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EVALUACIÓN DEL ESTADO EN LA CENTRAL TERMOGAS MACHALA A TRAVÉS MACHINE LEARNING

CONDITION ASSESSMENT AT TERMOGAS MACHALA POWER PLANT THROUGH MACHINE LEARNING

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Resumen

En este estudio se examinó la situación de la Central Termogas Machala. El desafío del proyecto consiste en superar grandes desafíos para asegurar la continuidad y asegurar un suministro eficaz de energía eléctrica, así como el uso eficiente de los recursos naturales y la reducción del impacto ambiental. La central termogas Machala opera en ciclo combinado, dispone de 8 unidades generadoras correspondientes a Machala I y Machala II, con una potencia total de 187 MW. Utilizando la programación en Python y la librería Pyomo para el proceso de optimización, se pudo examinar las variables de costos de combustible, potencia y energía eléctrica de la planta. La meta principal es reducir los costos de producción de energía eléctrica y las limitaciones están vinculadas a los costos de inicio, parada y el equilibrio de potencia. Además, para solucionar el problema se utiliza GNU Linear Programming Kit (GLPK), ya que el tipo de programación sugerido es entero lineal mixta. Mediante el análisis efectuado, se pudo determinar qué generadores térmicos pueden funcionar simultáneamente, elaborar planes de mantenimiento para la salida programada de estos generadores y determinar la energía total generada.

Palabras clave: Central Termogas, Ciclo Combinado, Pyomo, Python, Optimización.

Abstract

This study examined the situation of the Termogas Machala power plant. The challenge of the project is to overcome major challenges to ensure continuity and ensure an efficient supply of electricity, as well as the efficient use of natural resources and the reduction of environmental impact. The Machala thermal power plant operates in a combined cycle, has 8 generating units corresponding to Machala I and Machala II, with a total power of 187 MW. Using Python programming and the Pyomo library for the optimization process, it was possible to examine the variables of fuel, power and electric energy costs of the plant. The main goal is to reduce the electrical energy production costs, and the constraints are linked to the startup, shutdown and power balance costs. In addition, GNU Linear Programming Kit (GLPK) is used to solve the problem, since the type of programming suggested is mixed linear integer. Through the analysis carried out, it was possible to determine which thermal generators can operate simultaneously, to develop maintenance plans for the scheduled output of these generators and to determine the total energy generated.

Keywords: Combined cycle, Pyomo, Python, Optimization, Thermogas Plant.

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1. Introducción

In Ecuador, one of the regulatory entities is the Agency for the Regulation and Control of Energy and Non-Renewable Natural Resources (ARCERNNR) [1], whose objective is to regulate various strategic sectors of the nation. Among these is the electricity sector, which has several control directorates. The Directorate of Control and Distribution of Electricity Sector Commercialization (DCDCSE), which oversees the use of electricity-by-electricity distribution companies nationwide. One of the responsibilities of the directorate is the billing process, which contains a large amount of data. Another relevant factor that the management considers is energy consumption trends, this analysis optimizes the control procedures carried out by the management [2].

Nowadays, electrical energy is a very common type of energy worldwide, since it is used both in the industrial sector and in most homes [3]. Electrical energy can be generated in a variety of ways, so it cannot be categorized as a renewable or non-renewable energy source. However, most energy production is concentrated in specific locations, which we call power generation plants [4].

The application of various technological tools facilitates the improvement and automation of numerous manual processes that are still carried out in an impractical manner. Similarly, the use of data obtained by management facilitates the projection of the country's energy consumption [5]. Machine Learning is a field that encompasses various disciplines of knowledge, including Deep Learning, which offers a wide variety of models and algorithms for different purposes. Time series represent a challenge that can be solved by intelligence algorithms. These models focus on the ability to train on a volume of data and then predict values based on the training data [6].

The procedure of estimating energy intake in Ecuador's electricity sector poses considerable challenges due to the volume of data produced monthly by the electricity distribution companies [7], as well as the requirement for accurate analysis and projections. Although the Directorate of Control and Distribution of Electricity Sector

Commercialization (DCDCSE) has access to an enormous volume of data, manual handling and analysis of this data is laborious and error [8].

The challenge of the project is to take on major challenges to maintain continuity and ensure an efficient supply of electricity, the efficient use of natural resources and the reduction of the impact on the environment. The Machala thermal power plant operates in a combined cycle with a total capacity of 187 MW. Currently, electricity consumption is steadily increasing, and gas shortages at the Machala thermal power plant mean that there is not enough gas to cover the maximum production demand [9].

In contrast, today, electrical service from Ecuador's power generation plants has declined due to generation shortages [2], lack of maintenance and facility improvement plans. The Machala combined cycle thermoelectric plant has the ability to convert thermal energy from fuel gases into electrical energy. This term is applied to plants that use natural gases as fuel and use gas and steam turbines to produce electricity [10].

Machine learning, through the required calculations, can acquire behavioral patterns and algorithms, taking into account the PYOMO Python library to solve optimization challenges.

The objective of this study is to establish through an analysis the state estimation to optimize the operation of the Machala thermal power plant through the use of machine learning. The objective is: to establish the state estimation in the Machala thermal power plant [11]; to carry out the data collection of the Machala thermal power plant; to carry out a maintenance planning and operation tests of the Machala combined cycle thermal power plant, by means of a machine learning system [12].

2. Metodología

The process of construction and operation of the Machala Thermoelectric Power Plant began on July 2, 1996, with the signing of the Energy Development Corporation (EDC) with the State of Ecuador for the extraction of natural gas in the Gulf of Guayaquil.

The Machala thermogas production plant is located in the Bajo Alto sector of the Tendales parish, Canton El Guabo, Province of El Oro, as shown in Figure 1.

Fig. 1. *Machala Thermal Power Plant*

A. Characteristics of the Machala Thermogas Power Plant

The Termogas Machala power station operates with gas obtained from the Gulf of Guayaquil. Until early 2011, the plant produced more than 130 MW of energy that is supplied to the National Interconnected System (SNI) and subsequently distributed to end users.

The Machala thermoelectric plant has two zones known as Machala 1 and Machala 2, where, as shown in Figure 1, the 6FA natural gas production units are located, along with 6 TM2500 gas production units.

The Machala Gas Plant has the effective power detailed in Table I:

TABLE I. *EFFECTIVE POWER CENTRAL TERMOGAS MACHALA*

Central	Unit	Effective Power MW
Machala I	6FA1	64.6
	6FA2	64.6
Machala II	TM1	20
	TM2	20
	TM3	20
	TM4	20
	TM5	20
	TM6	19
Total		248.2

B. Development of the optimization model

Bender's algorithm is employed to solve the proposed optimization problem, this algorithm facilitates the solution of mixed integer nonlinear problems [13].

The GLPK tool, the GNU Linear Programming Kit, an open-source software intended for solving large linear optimization problems and mixed integer linear mixed programming problems, is used [14].

C. Problem master

It is stated in equation (1).

$$Minimizar_{x,\theta}\ f_1(x) + \theta$$

subject to

$$p(x) \leq 0$$

$$\theta \geq f_2\left(Y^{(v-1)}\right) + \sum_{k=!}^{n} \gamma_k^{(v-1)}\left(x_k - x_k^{(v-1)}\right) \qquad (1)$$

$$\theta \geq 0$$

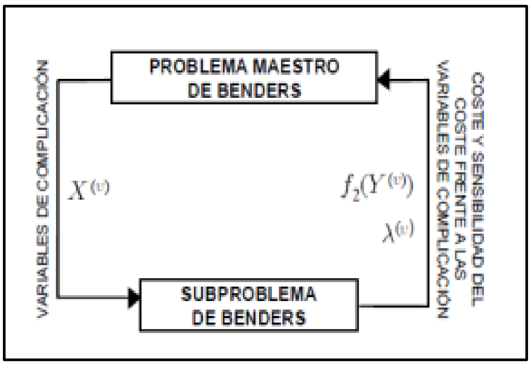
Where:

- θ: continuous and positive variable.
- v: iteration index of the algorithm.
- $x_k^{(v-1)}$: constant value taken by the variable x in the interaction v-1.
- $\gamma_k^{(v-1)}$: cost sensitivities associated with the constraints that set the value of the complication variables.
- $Y^{(v-1)}$: constant value taken by the variable when solving the Benders subproblem at iteration v-1 [15].

When solving the main problem, the value of the complication variables $X^{(v)}$ is obtained, as well as the value of the cost close to the subproblem $\theta^{(v)}$. The solution of the main problem incorporates the Bender Cuts procedure, which are constraints that iteratively reconstruct the initial problem function [16].

The solution of the main problem and the Benders subproblem demand a coupling process, also known as information exchange. The information acquired by the subproblem is transmitted to the main Benders problem to get a better interpretation of the original function, as illustrated in Figure 2 [17].

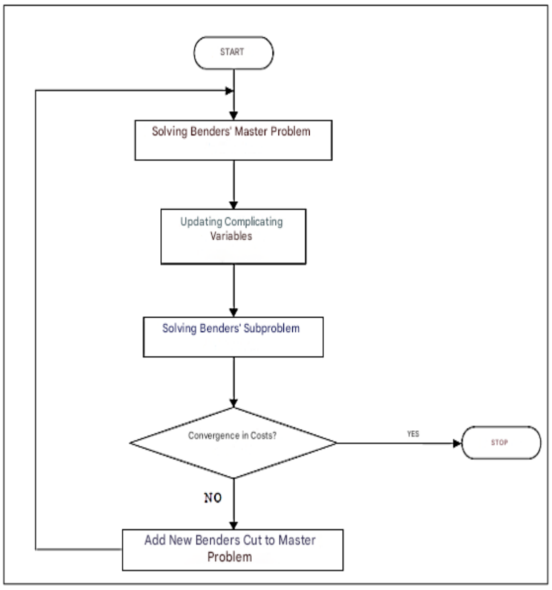
Fig. 2. *Bender Decomposition information exchange coupling process*



D. *End of iterations*

The iterative process ends when the lower and upper dimensions meet at a point or are close to the limits. In each iteration, the initial problem dimensions are updated with the resolution of the main problem and Benders' subproblem. The procedure in the algorithm depicted in the flow chart in Figure 3 [18].

***Fig. 3**. Benders decomposition flowchart*



E. Function Objective

The objective function (J) is represented in equation 2 [19].

$$J = \sum_{t=1}^{T} C_T \times P_g^t + C_g^A \times Y_g^t + C_g^P \times W_g^t \quad (2)$$

Where:

- U: binary coupling variable.
- C_T: total production costs.
- P_g^t: power generated by the g- th thermal unit at time t.
- C_g^A: fixed cost of starting the g- th thermal unit.
- Y_g^t: binary variable associated with the coupling of the g-th thermal unit (1= starts, 0= does not start).
- C_g^P: fixed cost of stopping the g-th thermo-unit.
- W_g^t: binary variable associated with the shutdown of the g-th thermo-unit (1= is shutdown, 0= is not shutdown).

F. Restrictions

The constraints are linked to a power balance linked to the minimum and maximum power limit of the thermoelectric generators. In addition, constraints are added by generator startup and shutdown costs, as discussed in equations 3 and 4 [20].

$$E_g^{mín} \leq E_g^t \leq E_g^{máx} \quad (3)$$

Costs

$$C_{on_d} \times Y_g^t \geq C_{on_d}\left(Y_g^t - Y_g^{t-1}\right) \quad (4)$$

$$C_{off\_d} \times W_g^t \geq C_{off\_d}(W_g^t - W_g^{t-1})$$

Where:

C_{on_d}: start-up cost of generating units.

C_{off_d}: cost of stopping the generating unit.

Y_g^t: binary variable associated with the coupling of the g-th thermal unit (1= starts, 0= does not start) [21].

W_g^t: binary variable associated with the shutdown of the g-th thermal unit (1= is shutdown, 0= is not shutdown).

In general, with respect to the coupling logic constraints for each thermal generator, it must be considered that:

a) If the thermal unit is coupled in period (t-1) and also coupled in period (t), the unit was already operating in (t-1).

b) If the thermal unit is coupled in period (t-1) and uncoupled in period (t), the unit stopped in (t).

c) If the thermal unit is decoupled in period (t-1) and coupled in period (t) then the unit was started in (t).

d) If the thermal unit is decoupled in period (t-1) and also decoupled in period (t) then no start-up has been performed [22].

For the programming the data expressed in tables 2 to 5 are used.

TABLE II. *DEMAND REQUIRED PERIOD 2015-2022*

YEAR	DEMAND [kW]
2015	800000
2016	560000
2017	780000
2018	890000
2019	450000
2020	560000
2021	630000
2022	660000

TABLE III. *FUEL CONSUMPTION PER KWH*

YEAR/TEAM	2015	2016	2017	2018	2019	2020	2021	2022
6FA1	4894.55	4889.3	5362.7	5776.85	4161.13	4193.44	4097.86	2310.39
6FA2	1343.29	4692.4	4964.54	4976.93	3929.96	1490.87	1569.73	1725.51
TM1	1667.91	1475.6	1274.79	621.01	617.99	1064.75	17.6	0
TM2	1356.64	1639.63	1145.69	589.72	337.86	553.61	277.54	357.43
TM3	1613.96	892.42	884.73	976.86	400.1	571.88	141.83	1065.48
TM4	1363.04	1538.02	1266.58	844.65	415.38	450.55	725.99	800.39
TM5	1053.41	940.94	987.83	263.06	406.54	802.06	1232.92	744.46
TM6	0	536.63	260.63	38.5	45.59	214.01	9.93	69.15

TABLE IV. *FUEL COST (CTVS/KWH)*

YEAR/TEAM	2015	2016	2017	2018	2019	2020	2021	2022
6FA1	0.0355	0.0356	0.0353	0.0354	0.0354	0.0354	0.0357	0.0359
6FA2	0.0355	0.0356	0.0354	0.0355	0.0354	0.0354	0.0358	0.0000
TM1	0.0354	0.0354	0.0353	0.0354	0.0355	0.0354	0.0358	0.0360
TM2	0.0353	0.0351	0.0352	0.0355	0.0355	0.0354	0.0358	0.0360
TM3	0.0355	0.0354	0.0354	0.0356	0.0355	0.0354	0.0358	0.0360
TM4	0.0354	0.0352	0.0352	0.0354	0.0355	0.0354	0.0358	0.0360
TM5	0.0354	0.0354	0.0355	0.0355	0.0355	0.0354	0.0358	0.0360
TM6	0.0000	0.0357	0.0360	0.0358	0.0357	0.0357	0.0358	0.0364

TABLE V. *NET ENERGY [KWH]*

YEAR/TEAM	2016	2017	2018	2019	2020	2021	2022
6FA1	427093.428	440357.486	488657.18	518791.565	373367.267	371937.467	353363.759
6FA2	416881.796	413944.236	437756.828	423601.971	325645.266	127765.249	0
TM1	124360.929	137677.276	117294.772	55594.8701	55099.1741	94424.8016	1527.73927
TM2	158781.925	154873.018	111942.123	54688.337	32153.8818	48659.9589	24353
TM3	126438.364	81491.3336	79474.252	84667.3063	35401.02	50720.6737	13038.4184
TM4	153224.101	143980.659	118878.266	75467.965	37558.7024	40089.3692	60928.7457
TM5	126964.984	86230.2578	94333.7723	22936.1118	37145.6809	67843.2518	100771.35
TM6	96792.5595	48149.9665	22075.1085	2993.16998	5.725097	18768.2382	6077.83474

3. Resultados y discusión

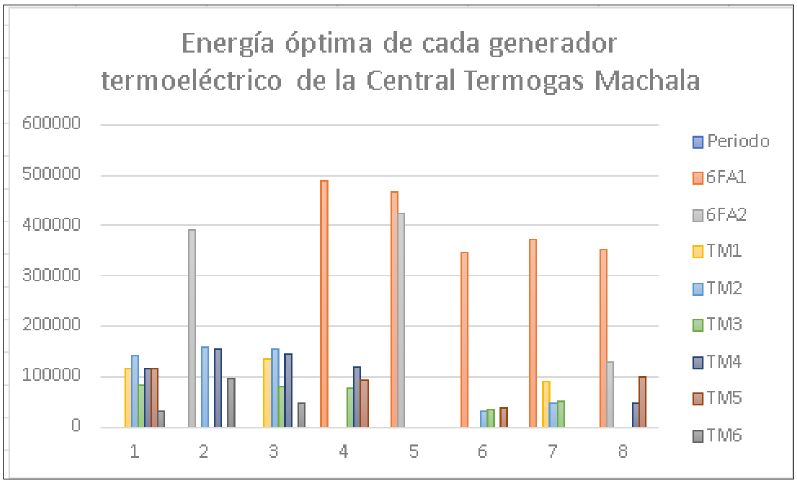
Mixed integer linear programming, performed in Python-Pyomo with the equations described in Section 2, yielded the results described in Table VI.

TABLE VI. *NELECTRIC POWER FROM EACH THERMAL GENERATOR AT TERMOGAS MACHALA THERMAL POWER STATION*

ENERGÍA ÓPTIMA [kWh]								
AÑO/EQUIPO	**T1**	**T2**	**T3**	**T4**	**T5**	**T6**	**T7**	**T8**
6FA1	0	0	0	488657.18	466398.03	345299.42	371937.47	353363.76
6FA2	0	392957.19	0	0	423601.97	0	0	128321.46
TM1	113940.22	0	133805.17	0	0	0	88681.9	0
TM2	141854.32	158781.92	154873.02	0	0	32153.88	48659.96	0
TM3	82611.31	0	79996.94	78130.78	0	35401.02	50720.67	0
TM4	114269.46	153224.1	143980.66	118878.27	0	0	0	47543.42
TM5	116394.39	0	0	94333.77	0	37145.68	0	100771.35
TM6	30930.3	95036.79	47344.21	0	0	0	0	0

In order to optimally satisfy the power demand of the plant, not all generators will operate simultaneously. Therefore, depending on the demand required, the generators will be coupled, as shown in the graph in Figure 4:

Fig. 4. *Optimal energy Machala Thermogas Power Plant*



- Period 1:

With a total electrical generation of 600 MWh, generators TM1, TM2, TM3, TM4, TM5 and TM6 are coupled, with a demand of 119 MW.

- Period 2:

With a total electrical generation of 800 MWh, generators 6FA2, TM2, TM4 and TM6 are coupled with a demand of 124 MW.

- Period 3:

With a total electrical generation of 560 MWh, generators TM1, TM2, TM3, TM4 and TM6 are coupled, with a demand of 99 MW.

- Period 4:

With a total electrical generation of 780 MWh, generators 6FA1, TM3, TM4 and TM5 are coupled with a demand of 125 MW.

- Period 5:

With a total electrical generation of 890 MWh, generators 6FA1 and 6FA2 are coupled, with a demand of 130 MW.

- Period 6:

With a total electrical generation of 450 MWh, generators 6FA1, TM2, TM3 and TM5 are coupled with a demand of 125 MW.

- Period 7:

With a total electrical generation of 560 MWh, generators 6FA1, TM1, TM2 and TM3 are coupled, with a demand of 125 MW.

- Period 8:

With a total electrical generation of 630 MWh, generators 6FA1, 6FA2, TM4 and TM5 are coupled with a demand of 170 MW.

A. Verification

The results are verified using the GAMS payment software. Figure 5 shows the information of both the problem and the SOLVE; 129 variables are examined, 137 constants are considered and there is an objective function.

Fig. 5. *Information on the problem posed.*

```
# ----------------------------------------------------------
#   Problem Information
# ----------------------------------------------------------
Problem:
- Name: unknown
  Lower bound: 242251.172551
  Upper bound: 242251.172551
  Number of objectives: 1
  Number of constraints: 137
  Number of variables: 129
  Number of nonzeros: 319
  Sense: minimize
# ----------------------------------------------------------
#   Solver Information
# ----------------------------------------------------------
Solver:
- Status: ok
  Termination condition: optimal
  Statistics:
    Branch and bound:
      Number of bounded subproblems: 5427
      Number of created subproblems: 5427
  Error rc: 0
  Time: 0.40218424797058105
# ----------------------------------------------------------
```

The image in Figure 6 shows the results obtained from the optimization process, the results when compared with Table VI are exactly the same.

Fig. 6. *Results obtained*

```
# ----------------------------------------------
#   Solution Information
# ----------------------------------------------
Solution:
- number of solutions: 1
  number of solutions displayed: 1
- Gap: 0.0
  Status: optimal
  Message: None
  Objective:
    obj:
      Value: 242251.17255100008
  Variable:
    E[G1,T4]:
      Value: 488657.18
    E[G1,T5]:
      Value: 466398.03
    E[G1,T6]:
      Value: 345299.42
    E[G1,T7]:
      Value: 371937.47
    E[G1,T8]:
      Value: 353363.76
    E[G2,T2]:
      Value: 392957.19
    E[G2,T5]:
      Value: 423601.97
    E[G2,T8]:
      Value: 128321.46
    E[G3,T1]:
      Value: 113940.22
    E[G3,T3]:
      Value: 133805.17
```

4. Conclusiones

Currently, the Termogas Machala power plant generates 630 MWh of electricity through the operation of thermal generators 6FA1, 6FA2, TM4 and TM5. In 2022, the TM6 generator is not in operation and, according to the research carried out, it will be put into operation with the expansion project by 2024.

The optimization was carried out based on fuel costs and the energy produced resulted in an ideal annual average of 242.25 MWh, which establishes an appropriate operation of the Thermogas Power Plant, with combined cycle. It is important to note that the average fuel cost is 0.036 ctvs/kWh.

According to the results obtained, the maintenance and tests to be carried out will depend on the coupling or not of certain thermal generators according to the required demand. For example, in period 6 the generators 6FA1,TM2, TM3 and TM5 are coupled, while in the same period they must be tested and the corresponding maintenance and tests must be carried out.

By implementing an algorithm using the Python programming language and the Pyomo library, it was possible to establish the coupling of heat generators according to the necessary economic dispatch and fuel cost.

The use of Bender's decomposition method is one of the many alternatives for solving mixed linear integer optimization problems, although it is more frequently used in education to explain the procedure necessary to solve such problems. Other algorithms can be used to solve these problems, although the one used in this study is less complicated and more effective in solving the problem.

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