Optimum operation of electric power generation resources

Administración Del Mercado Eléctrico (ADME)
Uruguay - Febrero 2023

1. Introduction to the Wholesale Electricity Market

The ADME is in charge of managing the Wholesale Electricity Market (WEM).

The WEM is the competitive field where Generators sell and Large Energy Consumers buy electricity. In order to operate in the WEM, they must be incorporated in ADME as Generator and Consumer Participants respectively.

To guarantee free competition and thus promote efficiency, the ADME must ensure non-discriminatory treatment to all Participants (both Generators and Large Consumers).

		Annual energy		Installed capacity	
		GWh 2021	GWh 2022	Plants	MW
Generation	Wind	4971	4763	41	1484
	Solar	436	438	18	238
	Biomass	1032	936	12	481
	Hydroelectric	5159	5522	4	1573
	Fossil fuels	2451	1282	5	1174
	Import	55	24		
	Total	***14104***	***12965***	***80***	***4951***

		Annual energy	
		GWh 2021	GWh 2022
Demand	National Demand	11187	11444
	Export	2844	1366
	Total	***14031***	***12810***

Fig. 1: Installed capacity, generation and destination of energy.

To ensure economic dispatch at all hours, the ADME maintains information on the variable generation costs of each generator and decides which ones and how much they will generate each hour. This is what is known as "solving the dispatch".

Currently (February 2023) 80 generators participate in the WEM, totaling an installed capacity of 4,951 MW. The National Demand was 11,444 GWh in 2022 with an annual growth expected between 2 and 3%. The tables in Fig.1 summarize the generation by source and destination of the energy generated in the years 2021 and 2022.

All Generators are, due to their own energy consumption, WEM Consumer Participants (in addition to being Generator Participants due to their generation). The state company UTE is the largest buyer in the WEM for the supply of energy to its Captive Demand (residential, commercial and industrial consumers subject to regulated electricity rates).

The ADME is in charge of carrying out the Energy Dispatch at Minimum Cost. This implies deciding at all times how much energy each power plant should generate and what the flow will be through the international interconnections (imports/exports to and from Argentina and Brazil).

To connect energy generation with consumption, electrical networks are used that are classified as Transmission System (voltage networks greater than 60kV) and Distribution System (low voltage networks). The operation of these networks are regulated services, with the company UTE being the Transmission and Distribution operator. By law, it must ensure open access to the networks and non-discriminatory treatment of the WEM Participants, charging for its service transportation/distribution rates (tolls) calculated and regulated by the Regulator.

1.1. The National Interconnected System (NIS) and The Demand

By National Interconnected System (NIS) we understand the set of generators, transformation/conversion stations, transmission and distribution networks that are available in the national territory, for the purpose of generating, transmitting and distributing energy to national consumers and delivering or receive energy in the interconnections with neighboring countries. The NIS is then the system that we are interested in operating.

By Demand we understand the energy to be supplied each hour to all consumers. The ultimate objective of the NIS operation is to supply Demand reliably at the lowest possible cost.

1.2. Fixed Costs, Variable Costs and Monomic Price

We call Fixed Costs those costs associated with equipment (power plant, transmission line, transformation station, etc.) that do not depend on the use of the equipment.

We call Variable Costs those costs associated with the use of equipment.

Investments in the electricity sector have the characteristic of being capital intensive and with construction periods of more than two years. For this reason, once an investment is installed, the investment itself and the costs necessary to maintain the equipment become Fixed Costs, in the sense that it does not depend on whether or not the equipment is used, they are costs to cover.

Variable Costs are those costs directly associated with the use of the equipment. These costs are usually associated with the cost of fuel (if it is a generation plant) and the variable costs of operation and maintenance associated with the wearthering of the equipment caused by its use.

Table 1: Example of Fixed and Variable Costs for different technologies. Prices in US$ from February 2023.

	Fixed costs(*) [US$/MWh]	Variable costs [US$/MWh]	Fuel
Combined cycle	25	193	Diesel(**)
Gas turbine	14	285	Diesel(**)
Wind	45	0	Wind
Solar	40	0	Solar
Biomass	85	60	Biomass
Hydroelectric	45	5	Water

(*)fixed costs are approximate for reference only
(**) with a barrel of WTI oil at 73.53 US$/bbl

In order to express the costs in a way that is comparable between the different equipment, its value is usually calculated per hour that the equipment is available and per unit (MW) of capacity available during the useful life of the equipment using a discount rate. (eg 10% per year in constant dollars). In this way, the values are calculated as those in Table 1. These values are approximate only to serve as an example. As can be seen, both Fixed Costs and Variable Costs are expressed in US$/MWh (dollars per megawatt hour) but both costs should not be confused. Fixed Costs are expressed in dollars per mega-Watt and per hour that said mega-Watt is made available (that is, it is for the available energy, not for the generated one) while Variable Costs are expressed in dollars per mega-Watt- hour of energy delivered.

Once a generation plant is installed, for the purposes of minimum cost dispatch, the only relevant thing is its Variable Cost of generation. By way of example, the wind and solar power plants have practically zero Variable Cost (zero for fuel and very low for operation and variable maintenance) for which they are energies that, if available, are dispatched with priority over any other.

Sometimes we talk about the Monomic Price of generation of a certain plant. This price is a complex to cover both Fixed and Variable Costs expressed in US$ per unit of energy delivered by the plant. In the jargon of the sector it is said that "Fixed Costs are energized". In order to calculate said Monomic Price, it is necessary to know what the Convocation Factor of the generating plant will be, that is to say, of the total energy that it could deliver (if all its available energy were accepted all the time), how much would actually be dispatched. By way of example, if the Convocation Factor of the Combined Cycle plants in table 1 were 20%, its Monomic Price would be: 25 / 0.2 + 193 = 318 US$/MWh

1.3. Marginal Cost of Generation

In each hour, the ADME orders the available generation resources from the lowest to the highest Variable Cost, thus creating what is known as "the Order of Merit". Depending on the Demand of the hour, the real-time operators dispatch the resources according to the Order of Merit until the Demand is covered. The Variable Cost of the most expensive resource dispatched in the hour is called the Marginal Cost of Generation. The Marginal Cost of Generation is then the cost that it would have to supply an additional MWh of demand in the hour.

1.4. Fault Generators

Failure (or Rationing) is understood as the impossibility of the system to cover the Demand. The non-supply of the required energy has a cost for the country associated with the loss of comfort (for example, not being able to watch the soap opera) of the users and the losses caused in the country's production chains (for example, losses due to interruption of industrial machinery). In order to quantify these costs, different methodologies are used in different countries and thus what are known as Failure or Rationing Costs are established. In Uruguay, the Executive Power sets by decree four Failure Lots (rationing depth levels) with their respective four Variable Costs associated with the energy not supplied. Table 2 shows the current values for the Failure Lots. The first lot of Failure is assigned a Failure Cost equal to the Variable Cost of the

Table 2: Costs of the four lots of Falla de Uruguay

	Failure Lots (Decree 195/2013)			
	1	2	3	4
Depth [%]	2%	5%	8%	86%
[US$/MWh]	CTR+10%	600	2400	4000

CTR thermal power plant (two 111 MW heavy duty aeroderivative turbines fed with diesel) plus 10% and has a depth equal to 2% of the Demand. Failure Costs reflect how much you are willing to pay to avoid said rationing and therefore, it is these values that determine the level of investments that will be made. High Failure Costs will lead to the installation of more equipment to avoid Failures and conversely, low Failure Costs will induce a lower level of investment.

To model this characteristic, in the programs used to optimize the use of resources (and to plan investments) the Failure Steps are represented as if they were simple generators with a Variable Cost equal to the corresponding Failure Cost. These Failure generators are what we call The Failure Machines. They are fictitious generators and in the results of the simulations, the generation that these generators have represents the energy that will not be supplied to the Demand.

1.5. Value of dammed water

Hydroelectric plants also have a quasi-zero Variable Cost. If the plant has a reservoir capacity, it is possible to use the water at the current time, substituting part of the resource that it marginalizes and thus saving the cost associated with the energy replaced by its Variable Cost or postponing the use of water (using the reservoir capacity) to substitute another resource with a higher Variable Cost in the future. Thus, the value of the water stored in each reservoir is defined as the cost that said water is able to avoid if its use is postponed for the future. ADME calculates the Value of Water for the Bonete, Palmar and Salto Grande lakes and these values are used to define the Order of Merit used for the dispatch in each hour.

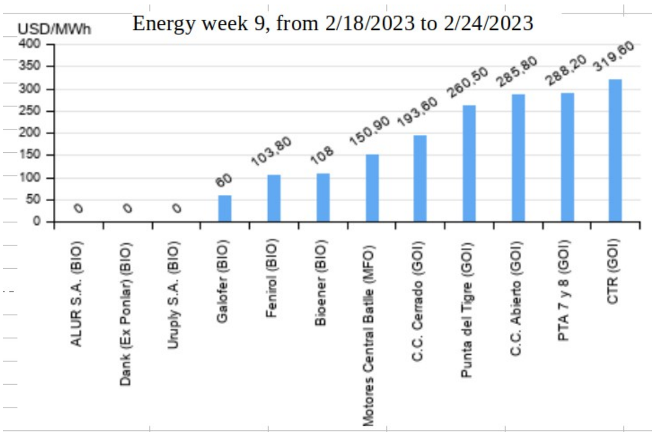

Fig. 2: Variable costs of thermal generation resources.

The calculation of the Water Value is carried out by solving what in mathematical jargon is known as a Stochastic Dynamic Programming Problem. ADME uses the Simulation of of Systems of Electrical Energy (SimSEE) platform developed by the Institute of Electrical Engineering of the Universidad de la República Oriental del Uruguay.

Dammed water value						
Día	Valor Bonete	Valor Palmar	Valor Salto	Control Bonete	Control Palmar	Control Salto
2023-02-21	319.6	288.2	288.2	-16.6	-38.0	-76.8
2023-02-22	319.6	288.2	288.2	-20.6	-37.7	-75.0
2023-02-23	294.4	252.1	224.3	-	-	-
2023-02-24	289.5	256.1	240.2	-	-	-
2023-02-25	285.3	255.6	246.4	-	-	-
2023-02-26	287.6	256.6	245.8	-	-	-
2023-02-27	291.4	258.9	251.3	-	-	-

Fig. 3: Damped Water Value

1.6. Order of Merit

As already mentioned, ADME keeps track of the Variable Costs of the different generators and calculates the Value of Reservoir Water for hydroelectric plants with reservoirs (Bonete, Palmar and Salto Grande). This information is published on the ADME website(https://adme.com.uy). Fig.2 shows the Variable Costs corresponding to energy week 8 of the year 2023 for thermal generation plants. Fig.3 shows the

Damped Water Values for the same week. As can be seen, in this particular week, the values of water are of the order of diesel turbines. This is because we are going through an extended drought and therefore the programs that optimize the use of resources perceive that the dammed water has the corresponding value to replace generation with diesel from diesel turbines.

To establish the Order of Merit, energy from wind and solar sources is considered to have zero Variable Cost, as well as energy produced from biomass by industrial processes. Eventual generation forcings (for example, the need to maintain a minimum ecological flow in hydroelectric plants) are also considered with zero Variable Cost. After the zero Variable Cost resources, the resources corresponding to the thermal and hydraulic power plants ordered by increasing Variable Cost are considered, considering for the hydraulics the Value of Water as its Variable Cost. Fig.4 shows the Order of Merit of dispatchable resources with variable cost greater than zero corresponding to 2/21/2023. As can be seen in said figure, hydroelectric plants with Variable Costs equal to those established in the table of Fig.4 appear.

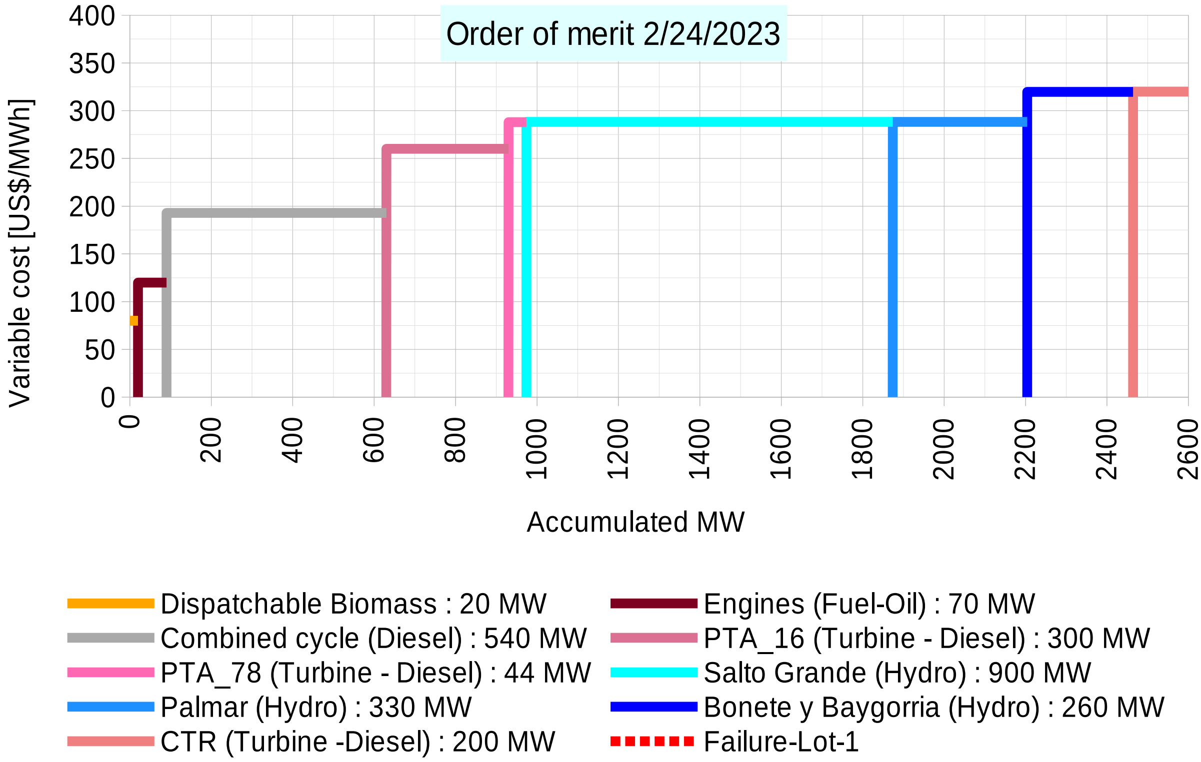

Fig. 4: Merit order of resources with Variable Cost greater than zero (@2/21/2023)

At any time of the day in the example (2/21/2023), NIS Operators will subtract from the Demand value the energy available from zero variable cost resources (forces, wind, solar and self-dispatched biomass) thus calculating what is known as the Net Demand and using the Order of Merit of Fig.4 will give the corresponding dispatch orders. By way of example, if the expected Demand for the hour 18:00 was 1,800 MW and the sum of the zero variable cost resources was 200 MW, 1,600 MW of resources with Variable Cost greater than zero must be dispatched. In accordance with the Order of Merit, all the power available from the plants must be dispatched: Dispatchable Biomass, Engines, Combined Cycle, PTA_16 and PTA_78 and what is necessary from the Salto Grande plant to complete the 1600 MW. In this example, the power station that would be marginalized is Salto Grande and the Marginal Cost of Generation would be 288.2 U$S/MWh. In the example, the resources PTA_78, Palmar and Salto Grande have the same Variable Cost, so they are "interchangeable" in the Order of Merit and the Operator will dispatch them in the order that is safest and easiest for the operation in real time.

1.7. Spot Price and Contracts

At the end of the month, the ADME sanctions the Spot Price of energy for each of the hours of the month as the hourly Marginal Cost of Generation with a ceiling price of 250 US$/MWh. This ceiling price is set by the Executive Power.

The Spot Price is used to value all the injections and extractions of energy in each of the hours of the month. From this valuation, the Participants that inject energy will result with credits on the market and those that withdraw energy with debits. If there were no contracts, these valuations would be directly the amounts to be received/paid by each participant.

The ADME publishes every hour a Spot Price forecast for the next 168 hours as shown in Fig.5.

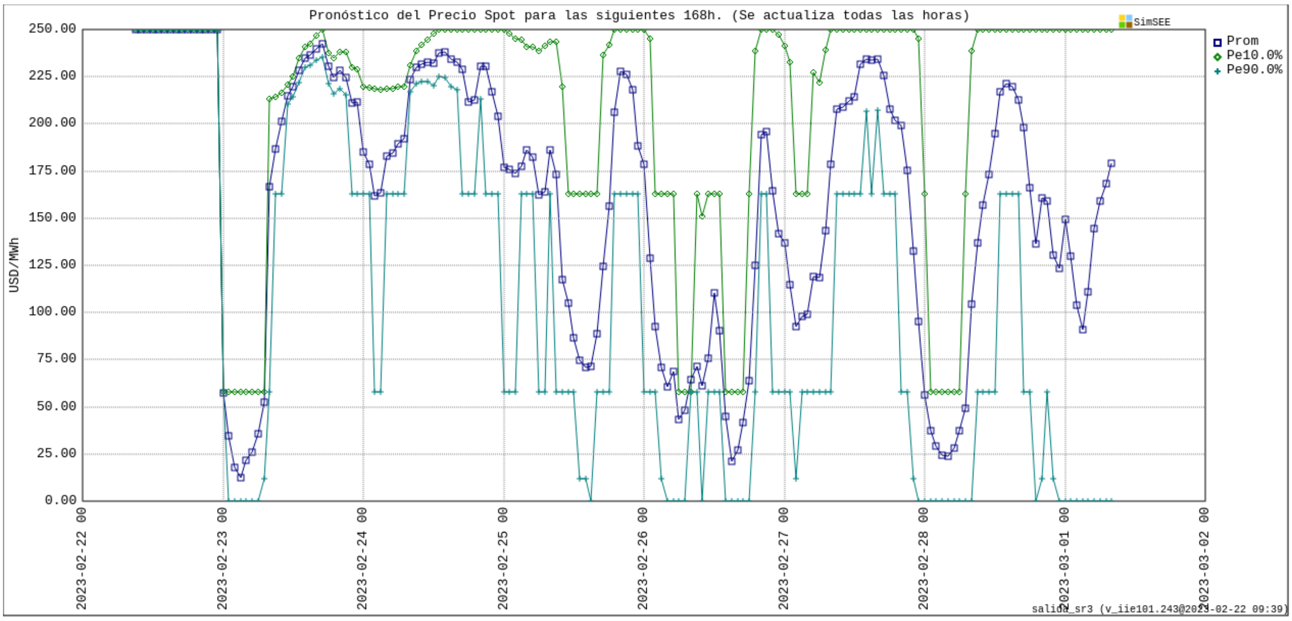

Fig. 5: Example of Spot Price Forecast for the next 168 hours

As can be seen, the Spot Price presents significant volatility, going from zero values when wind and solar resources abound to values equal to the ceiling price when these resources are scarce and Demand is high. This volatility of the energy price in the Spot, translates into a high volatility in the potential income of the generators and the payments of the consumers. Since the risks are complementary, the contracts between generators and consumers, setting a fixed price for the energy traded in the contract, serve as risk mitigation instruments.

At the end of the month, the ADME values the energy injected and withdrawn at the hourly Spot Price and subtracts from them the energy agreed in contracts between the parties, thus reducing the total to be collected/paid by each Participant for their injections/ extractions in the Spot Market.

Through simulations, the ADME calculates the exposure to payments in the Spot of each Participant, taking into account the contracts that it has for the following twelve months and as a way of guaranteeing payments, it must require the Participants to maintain a guarantee equal to the sum of the two months with the highest exposure.

2. Operation programming

The ADME carries out the Operation Programming (planning the use of generation resources to supply the Demand) in different time horizons: Long Term (next years), Medium Term (next months) and Short Term (next hours and days).

The objective of Long-Term Programming is to detect whether the supply of future Demand is assured based on the projection of Demand growth, the withdrawals of generating plants due to obsolescence and the income of new generation plants of the projects that are informed. In the event of detecting that there is a future risk of supply, the ADME must inform the Executive Branch and, if necessary, can carry out tenders to ensure that new generation plants are installed.

The purpose of the Medium Term Programming is to value the water from the lakes in a time horizon that covers the changes of the seasons and to generate forecasts for the consumption of Fuel Oil and Diesel, forecasts that are necessary to program the imports necessary to supply said fuels.

The purpose of Short Term Programming is to generate the Order of Merit in order to have the necessary instructions for the real-time operation of the system. For this stage of programming, Demand forecasts, hydraulic contributions to dams, wind and solar generation are essential.

2.1. Forecasts

a) Demand Forecasts

The Demand has an important dependence on the temperature, being greater at low and high temperatures since when we move away from the comfort temperature we spend energy to heat or cool the environments. Demand also strongly depends on the level of activity, being higher on business days than on weekends and holidays.

ADME has developed its own Demand forecast model that provides a probabilistic forecast of the behavior given the temperature forecast and the types of days to be considered according to the calendar. A description of the model can be found in [1]

b) Water inflows Forecast

The annual hydroelectric generation in Uruguay varies between 3,500 and 10,000 GWh depending on the rainfall of the year. What is not covered with hydroelectricity must be generated with another resource and therefore such significant volatility in the hydroelectric resource translates into significant volatility in generation based on diesel and fuel oil. Uruguay's rainfall regime is conditioned by the iN34 index, which measures the anomaly of the surface temperature of the Pacific Ocean in the region known as N3.4. This conditioning has been incorporated into the ADME models based on the joint work with the IMFIA [2].This modeling allows the information from the iN34 forecasts generated by international research centers to be incorporated into the stochastic models that generate the synthetic flow series that we use in the simulations in the Medium and Short Term programming. At ADME we consider the iN34 forecasts published in: https://iri.columbia.edu/our-expertise/climate/forecasts/enso/current/

In the Short Term, there are precipitation forecast ensembles (generated by global models of the atmosphere such as GFS or ECMWF) and a basin model developed jointly with IMFIA [3]. In the works [4] and [5] the methodology for the integration of the information of the forecast ensembles in the simulation tools used in ADME for dispatch programming is explained.

c) Wind and solar generation forecasts

Wind power generation forecasts are of paramount importance for the programming of the Short Term dispatch in Uruguay. In particular, they determine in practice the need or not for the dispatch of the thermal power plants in the following days and, above all, they determine the advisability or not of dispatching the Combined Cycle, a plant that due to its size and minimum technical restrictions, is only convenient for its Dispatch if days with low wind production are forecast.

ADME has contracted the Meteoblue company to forecast the meteorological variables (wind speed at 80m, solar radiation, temperature, pressure, etc.) at the locations of each of the wind and solar generators distributed throughout the National territory. These forecasts are downloaded twice a day and provide the hourly series for the next 10 days expected for these variables. These forecasts feed models developed in ADME of the wind and solar farms to obtain the forecast of energy available in each plant.

The work [6] shows the application of Neural Networks to the creation of forecast models of the probability distributions of the generation from the forecasts of the meteorological variables and the real series of production of the wind farms. The same methodology is applicable to solar generation plants.

2.2. Robots Vates

Fig. 6: Robot Vates_MP and Robot Vates_CP

The process of programming the operation is a task that is carried out continuously. New information on the state of the system is arriving all the time, such as the registered values of the Demand, of the inflows to the dams, which generation units are available and which are not, and new information on the forecasts of water inflows, Demand and wind and solar generation. To carry out this task in ADME we create two Robots that are running all the time.

a) Robot Vates_MP

The Robot Vates_MP runs twice a day and optimizes the use of resources in the horizon of the next three months. To do this, it incorporates the information available on the current state of the system and the latest information available on forecasts and optimizes the operation and simulates 1000 chronicles (realizations of the stochastic processes represented), with a daily step (subdivided into four groups of hours of equal Net-Demand requirement to adequately represent power constraints), the optimal operation for the next three months.

The results are published on the ADME website at the address:

http://latorrex.adme.com.uy/vatesmp/?C=M;O=D

As an example only, Fig.1 shows the expected evolution of the Rincón de Bonete lake in expected value and for different probability cuts.

The Vates_MP generates the Medium Term Operation Policy that serves as initialization for Vates_CP as described below.

Of the information generated by Vates_MP, the most used is the Operation Policy, which is needed by Vates_CP (to have future information), the expected evolution of the level of the Rincón de Bonete lake and the forecast of diesel and fuel oil consumption (necessary to schedule fuel imports that require at least 45 days in advance).

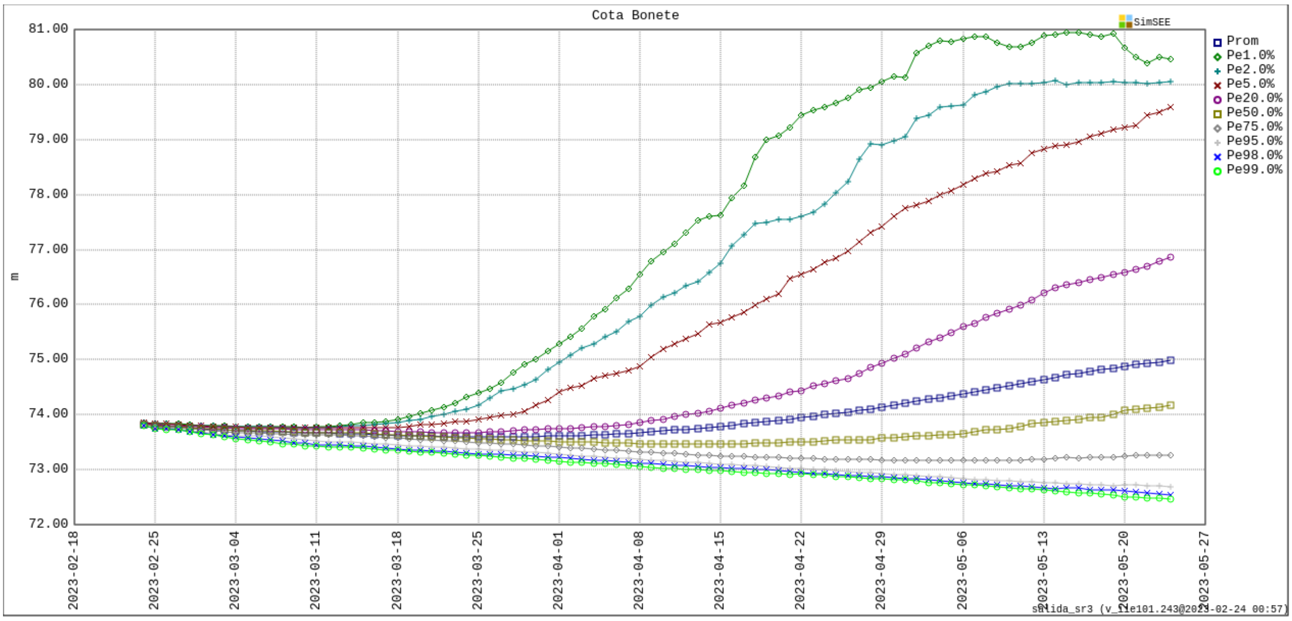

Fig. 7: Expected evolution of the Bonete lake level (VATES_MP@24/2/2023)

b) Robot Vates_CP

Vates_CP runs every hour assimilating the available information on the system status and forecasts and optimizes and simulates the operation of the next 240 hours with hourly detail. Every hour, at the end of the simulation, Vates_CP publishes the information on the ADME website. As an example, Fig.5 corresponds to an output from Vates_CP that is updated every hour at https://adme.com.uy

The generation forecast graph by source is published on the same page, as shown in Fig.8. By clicking on the figure you access the complete set of corresponding Vates_CP outputs and you can navigate to see the results of the simulations of previous hours and days.

It is from the results published by Vates_CP that the information that determines the Order of Merit with which the system operation will be carried out comes out.

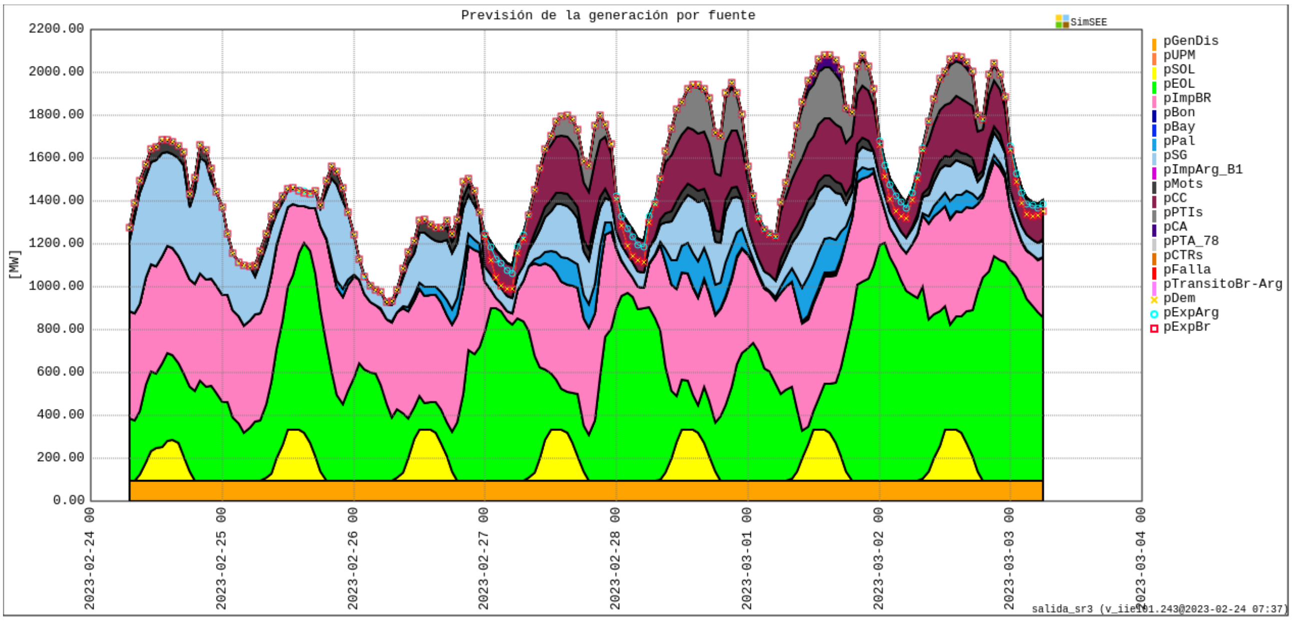

Fig. 8: Generation forecast by source in expected value (Vates_CP@2/24/2023 07:37)

c) Robot Vates_OI

This Robot is in the start-up process and will solve the dispatch of the next twenty-four hours with a ten-minute step, assimilating information from the forecast of solar generation in that horizon provided by satellite image processing by the Solar Energy Laboratory of Uruguay. This Robot will allow to have information in quasi-real time useful to anticipate the necessary resources to maintain the instantaneous balance of power.

3. Bellman's Curse and AI-Vates

The optimal operation of a system with energy storage capacity (reservoired water) falls within the category of optimal operation of dynamic systems and in control theory is what is known as a Stochastic Dynamic Programming Problem. In 1957 Richard Bellman at work [7] presented an elegant (and simple) solution to the problem of obtaining the Optimal Control Policy of a dynamical system method which is known as Bellman's Recursion.

Given that the decisions of the present affect the future, the Optimal Policy, for example of the use of water from a lake, is one that balances the benefits of using water in the present (by stopping using diesel for example) against over- cost of the future because you will not have that water.

3.1. System state and system model

State X is understood as the vector that contains every information from the past of the system relevant to calculate its future behavior if the future inputs of the system are also known.

In order to model the system, an equation must be achieved that describes the State Evolution in each time step k if the State X_k at the beginning of the time step, the vector of uncontrollable inputs r_k and the control vector u_k are known. The Evolution Equation has the form:

$$X_{k+1}=f(X_k,u_k,r_k,k) \quad , \qquad (1)$$

To complete the model, we need the equation that allows us to calculate the cost incurred in each time step (or stage) that will have the form:

$$c_k=c(X_k,u_k,r_k,k) \quad , \qquad (2)$$

We call Operation Policy, the set of rules/criteria that allow the Operator to set the control vector u_k if it knows the state at the beginning of the step and the non-controllable inputs. This equation will have the form:

$$u_k=PO(X_k,r_k,k) \quad , \qquad (3)$$

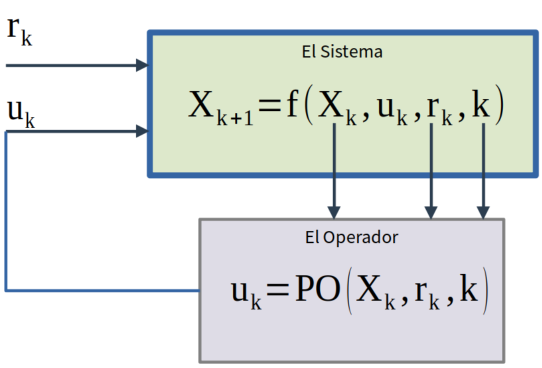

Fig. 9: Operator controlled system

Fig.9 shows the block diagram. A block with The System that is attacked by the input vectors r_k and u_k and the block of The Operator that feeds back to the system using an Operation Policy.

The Future Cost (or cost of the future operation) can be calculated from (2) by adding:

$$CF(X,k)=\sum_{h=k}^{\infty} q^{h-k} c_h \quad , \qquad (4)$$

Where c_h corresponds to the costs of each step calculated with (2) and the factor q is an update factor for money so that the sum represents the present value of the future cost of operation.

3.2. Optimal Policy

Given any function of the type (3) we can use it as an Operation Policy and simulating the operation of the system, with that Policy and for many possible realizations of the non-controllable inputs, calculate the expected value of the Future Cost (4) in the set of simulations $\langle CF(X,k)\rangle_{\{r_k^j, r_k^j+1, \ldots\}_j}$. We will say that an Operation Policy is better than another if it results in a lower expected Future Cost.

The problem of finding an Optimal Policy is then posed as the search for the function of type (3) that minimizes the expected value of the Future Cost:

$$\min_{PO} \langle CF(X,k) \rangle_{\{r_k^j, r_k^j+1, \ldots\}_j} \quad , \qquad (5)$$

3.3. Bellman's recursion

Richard Bellman published in 1957 the book Dynamic Programming [7] in which he proposes an elegant method for determining an Optimal Policy. The method is based on observing that the sum (4) that allows calculating the Future Cost for a trajectory, can be broken down into the stage cost of the first step plus the Future Cost of the same trajectory from the state reached at the end of the first step, multiplied by the update factor q :

$$CF(X_k, k) = c_k + q\, CF(X_{k+1}, k+1) \quad , \qquad (6)$$

where X_{k+1} is calculated with the state evolution equation (1).

Considering the expected value over the set of simulations, the optimization problem (5) can be restated as:

$$CF(X_k, k) = \left\langle \min_{u_k} \left[c(X_k, u_k, r_k^j, k) + CF(X_{k+1}, k+1) \right] \right\rangle_{\{r_k^j\}_j} \quad , \; (7)$$

Observe that, posed in this way, the problem can be read as: *If I know the Future Cost* $CF(X_{k+1}, k+1)$ *corresponding to the optimal operation for any state* X_{k+1} *from the time step* $k+1$ *then, if I can assume at the beginning of step* k *that the non-controllable inputs* r_k^j *are known, I can calculate the Future Cost corresponding to the optimal operation from the state* X_k *at the beginning of step* k *by solving (7).*

This algorithm is known as the Bellman Recursion and it allows calculating, walking backwards in time, the $CF(X,k)$ function from the $CF(X,k+1)$ function.

Observe that when solving the minimization problem, given a value of the uncontrolled inputs r_k^j , optimal control is obtained and therefore:

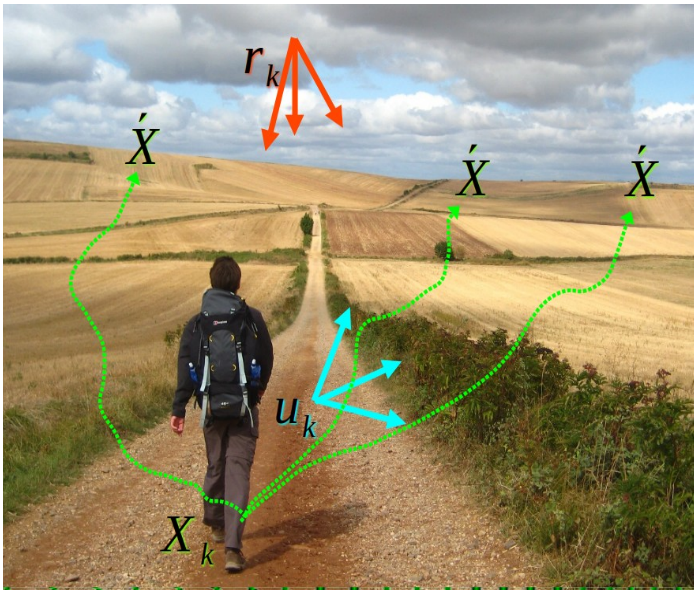

Fig. 10: Minimize stage cost plus Future Cost from the state reached at the end of the stage.

$$u = \arg\min_{u} \left[c(X_k, u, r_k^j, k) + CF(X_{k+1}, k+1) \right] \quad ,(8)$$

is an optimal Operation Policy.

In short, the information necessary to determine the Operation Policy is embedded in the Future Cost function. $CF(X,k)$. Observe that in solving (8) the result does not change if we add a constant to the $CF(X,k)$ function and therefore we can say that the relevant information for the optimal Operation Policy (the one obtained by solving (8)) is found in the δCF variations at the end of the time step caused by the δX variations of the state during the time step.

This result can be expressed in a simple way with the help of Fig.10. Imagine that the Walker is The System and that it is at a given position X_k at the start of time step k . And that resolving the energy dispatch for the time step of time implies walking to the horizon. Imagine also that the height of the horizon corresponds to the expected value of future optimal operation once each point (state) of the horizon is reached. Then, the minimization problem is nothing more than finding the control vector u_k that minimizes the sum of the cost of walking to the horizon (stage cost) plus the height of the horizon (future cost from the point reached).

In the same publication, Bellman states that the algorithm suffers from what we now call Bellman's Curse of Dimensionality. This curse arises from the combinatorial explosion of the cases to be solved in order to build for each time step the representation of $CF(X,k)$ solving (7). Assume, by way of example, that the dimension of the state space is N_x and that each dimension is discretized in 10 positions and that the vector space of uncontrolled inputs has dimension N_r and that each dimension is discretized in 5 positions. If, in addition, the number of time steps to be solved is N_k , then the minimization problem (8) will have to be solved $10^{N_x} \times 5^{N_r} \times N_k$ times. As can be seen, each state variable multiplies the number of problems to be solved by the number of positions in which said variable is discretized (the same with the exploration of the space of non-controllable inputs) and obtaining the Operation Policy using the Bellman recursion quickly becomes intractable.

Generation system operators have always fought against Bellman's Curse. This is the main reason why the Operation Programming is managed in different time horizons (long, medium and short term) in order to use a greater time step and a smaller dimension of the state in the Long Term, and gradually increase the degree detail in the short term. The Operation Policy (Future Cost function) of the Long Term $CF_{LP}(X^{LP}, k^{LP})$, serves as initialization of the Future Cost function at the end of the Medium Term horizon $CF_{MP}(X^{MP}, k_{Final}^{MP}+1) \Leftarrow CF_{LP}(...)$ to start from there (walking backwards in time) the Bellman recursion which allows us to calculate $CF_{MP}(X^{MP}, k^{MP})$ which in turn serves as the initialization of the Future Cost function to apply the Bellman recursion in the short-term horizon. In past decades, system operators with many water reservoirs (state variables) were the most affected by this problem. Currently, with the massive incorporation of wind and solar energy, which add variability at daily and hourly scales, any energy store becomes relevant, consequently increasing the number of state variables to be managed.

Of the tools currently in use, the following stand out:

- SDDP: Stochastic Dual Dynamic Programming. Extensive use in Brazil (system with many water reservoirs). It is an elegant weapon for fighting the Bellman's curse. But having to represent the stochastic loses power.
- Plexos: uses the technique known as "Rolling Horizons". This technique involves scanning a time horizon by simulation, selecting an action to take, moving forward one time step, and repeating the process. It solves well the operation of systems with time constants similar to those of the forecasts, but it is not good at obtaining the operation policy of systems with large lakes.
- SimSEE: It uses the classic Bellman recursion for which it suffers from the Curse, but it has a technology of stochastic models of Correlations in Gaussian Space with Histogram (CEGH) that allows it to introduce reductions in the state space of stochastic processes and also to assimilate in a simple way the information of their forecasts.

- SimSEE_IA: In the testing stage at ADME, it uses machine learning techniques to build an Operation Policy based on a continuous learning loop, thus escaping Bellman's curse.

3.4. SimSEE_IA, VatesIA_MP y VatesIA_CP

In 2020 the research project was completed: ANII-FSE_1_2017_1_144926 - "Investment planning with variable energies, network restrictions and demand management"

of the ANII Energy Sector Fund (2018-2020), a project that we renamed "El Tractorcito". Web page: https://simsee.org/investigacion/tractorcito.html.

Imagine something similar to Fig.10, but that the terrain is rugged, full of obstacles, ravines, etc. and that then, instead of going on foot, he goes on a Tractor (an all-terrain machine). The project creates a simulation environment, using the SimSEE platform, in which an agent (the individual with the tractor) has an Operation Policy and is then allowed to "test" and learn from experience how to improve their Policy. of Operation. This new platform that incorporates Artificial Intelligence to SimSEE is what we call SimSEE_IA.

This new SimSEE_IA platform was successfully applied to the modeling and simulation of the set of countries Argentina, Brazil, Paraguay and Uruguay [8]. The system was modeled with 76 state variables (75 reservoirs plus the iN34 index).

Currently, at ADME we already have the VatesIA_MP and VatesIA_CP Robots operating in parallel with the Vates_MP and Vates_CP Robots, which are the versions with Artificial Intelligence applying the SimSEE_IA platform instead of Bellman recursion.

In particular, the Robot VatesIA_CP uses a model with hourly detail of the Combined Cycle Power Plant that has represented, with state variables, the purging process of the steam circuit and heating of the steam turbine, a model that is impossible to use in the version classic Vates_CP due to Bellman's Curse.

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