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Modeling of a Hybrid Electrical Network Under the Constraint of Availability of Energy Sources by a Dynamic Bayesian Network

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ABSTRACT

As the world's energy shortages worsen, countries are starting to exploit renewable energies for which solar power becomes the first choice. Considering the insufficiency of hydraulic and thermal resources in Mali, the hybrid system photovoltaic coupled at the grid is necessary and natural. The present study aims to increase the contribution of renewable energy sources to the national electricity production of Mali, and to pave the way for a good supply of electricity, ensuring the sustainable development of the economy and society of Mali. A preliminary analysis defines the technical, economic and environmental conditions for the implementation of 30 MW solar power plants at three points of Mali's energy interconnection network. It can be a first contribution to demonstrating the feasibility of an integrated and self-sufficient energy model in this country. The power of 30 MW is compatible with the capacity of the interconnected network of Mali to absorb the electrical energy produced. For the location of the sites, several criteria have been taken into account for a definitive implementation (local climate conditions, proximity to the interconnected network, source of cooling water, social and environmental impact of the project).

Keywords: Photovoltaic System, Modelling, Hybrid, Grid, Management, Bayesian Network.

INTRODUCTION

In a rapidly changing global energy context marked by a decrease in conventional fossil energy resources and ever-increasing greenhouse gas emissions, the development of renewable energies remains a way to limit the effects of human activity on global warming. Of all renewable energies, solar photovoltaic (PV) is of particular interest for Africa, since it has a sizeable cosmic deposit.

Since the 1980s, Mali, in cooperation with many development partners, has initiated various development projects and programs to increase the use of renewable energy sources. This strategy combines efforts to reduce poverty, validate national energy resources, guarantee long-term security and environmental sustainability of energy supply.

Given the rapid increase in fuel prices imported, renewable energy sources are of growing interest. These renewable energy sources environmentally friendly are abundant in Mali and are becoming a more and more competitive and essential precondition for the development of Malian society. Currently, electricity demand is increasing by about 10% per year, and fuel transportation increased even more (African Bank for Development 2010). This situation results in enormous difficulties for the Malian government and national operators and seeks to reduce imports of fossil fuels, as well as for the public utility and private investors striving to provide enough electricity at a reasonable price.

Much of the energy generation comes from large-scale hydro-electric power station produced on the Senegal and Niger rivers, but small and medium diesel generators still provide about 20% of the total output. Even though interconnections are planned, and installed to meet part of the demand with electricity produced from natural gas in Ghana and Côte d'Ivoire, there are still good political and economic reasons to exploit the country's abundant renewable energy resources, such as hydro-energy, solar energy, and wind energy. At the end of 2012, cumulative global installed capacity is estimated at more than 100 GWc according to the European Association of the Photovoltaic Industry (EAPI, 2013) [1].

In this context the realization of large-scale solar power plants connected to the electricity grid is pertinent. Besides, once these hybrid power plants realized, the problem of managing solar energy produced according to the availability of the irradiation solar poses a significant problem.

Several studies have been conducted on PV solar plants installed around the world. (Kymakis et al., 2009) conducted a study on the performance analysis of a plant connected to the 171.36 kW grid on the island of Crête in 2002 [2]. (Makrides et al., 2010), evaluated thirteen different photovoltaic technologies in two localities (Nicosia, Cyprus and Stuttgart, Germany), all connected to the network with a nominal power of 1 KWc [3]. A study by (V. Sharma et al., 2013) focused on evaluating the performance of different rows of PV technologies consisting of polycrystalline silicon, thin film, amorphous silicon at the Solar Energy Center in India [4]. (HASSAN et al., 2014) evaluated the performance of a 300 KWc solar photovoltaic power plant connected to the network at DJIBOUTI using the various methods [5]. (Yang et al., 2015) analyzed the reliability of a single-phase converter with reactive power injection at night, considering mission profiles [6]. (Huai et al., 2016) have made a new approach to the study of reliability [7]. (Frede et al., 2017) conducted a study on the reliability of renewable energy systems [8]. (Victor et al., 2018) did a design study and selection of reliable converters for PV applications connected to the grid [9]. (Sangwongwanich et al., 2018) discussed a study of the power control flexibility of solar systems [10]. (Alberto et al., 2018) studied an autonomous photovoltaic system in an urban area of Mexico [11]. (Chen et al., 2018) did a study on the reconfiguration of a multi-state converter [12].

Most of the studies have been carried out on the evaluation of the performance of solar power plants, the reliability of the converters and the maximum power point tracking for installed PVs.\\

Our work will be focused on modeling the availability of solar production, to help the dispatcher, predict a reliable estimate of purchases from Manantali and the interconnection of Côte d'Ivoire suppliers using the Bayesian network to provide the interconnected system to meet three essential requirements: stability, economy and above all continuity of service. This is not always the case, because the network is often exposed to incidents that can interrupt this service and cause significant financial losses for industry and inconvenience for ordinary consumers. Our major contribution has been to combine analytical and probabilistic models with the Bayesian network in order to have a real decision-making tool that will allow the dispatching service to make better purchasing precision for energy and thermal productions. The objective is to reduce the overall costs of production and the emission of greenhouse gases. For the simulation, we have considered three scenario cases. The first scenario is to maintain thermal production as we have found to see the impact of solar production on the economic and ecological level. The second scenario is to maintain the energies purchased by allowing solar productions to reduce thermal productions with the same objectives that the first scenario. The third scenario is to play simultaneously on thermal production and purchased energy to allow the dispatching service to reduce economic and ecological impacts as much as possible. We have applied our approach on the interconnection networks of Mali.\\

The rest of the paper is structured as follows: in section 2, the material and the methods are discussed, in this section we have made an overview on the grid connected at PV systems and Bayesian Networks in subsections 2.1 and 2.2; a Bayesian estimate approach has been discussed in subsection 2.3. A case study has been done in subsection 2.3. The results of simulation on the best prevision were presented in section 4 to finish with a discussion and conclusion in section 5.

MATERIALS AND METHODS

Topology of an Interconnected Network

An interconnected network of electrical energy is a system including sources of production, transport and interconnection systems, posts of distribution and dispatch energy, and consumption points (customers).

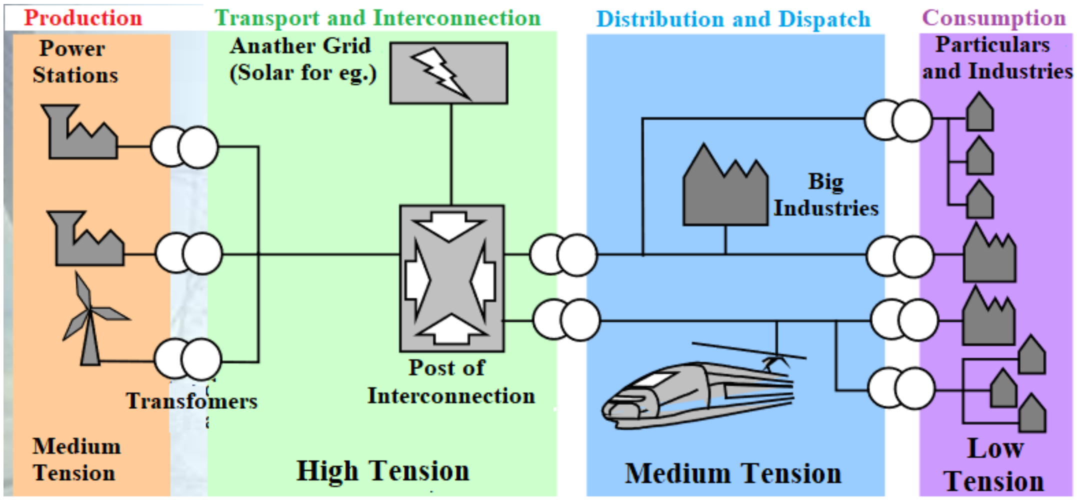


Figure 1 : Structure of an interconnection network from production energies to consumption

Electric Power Production:

It is the transformation of mechanical, thermal, chemical, wind or solar energy into electrical energy. Power stations are diverse and classified into conventional "classic" sources and renewable energy sources. Conventional power stations constitute the overwhelming majority of the power supply of existing networks, in which renewable energies have still a little place. They will stay in service for a long time to ensure the transition to an electrical system where renewable energies (RE) will take an increasingly large share. The conventional sources considered here are carbon or nuclear fuels of fossil origin, the power of which obtained in power plants can be flexibly controlled by an operator and then shipped through a network. However, RE sources are "intermittent" because the energy obtained fluctuates over time.

Transport and Distribution:

Transport and distribution networks link power stations to consumption points. They transport electrical energy in the form of three-phase alternating current characterized by: a specific frequency, voltage levels and termination couplings. The frequency is normalized and has only two values which are 50Hz and 60Hz. The voltage levels are distributed from the standardized values in **table 1**, which group together high voltage networks level(B) (HTB which is divided by a Very High Voltage (THT) network and a High Voltage (HT) network), high voltage networks level A (HTA, also called Medium Voltage (MT) network) and low voltage networks (BT) (European standard). Compliance with these values guarantees the safety of installations.

Table 1 : Voltage levels normalized.

Networks	Use	Normalized voltages
HTB	High voltage lines for National Transport and interconnection	225 KV/400 KV (THT) 90 KV/ 63 KV (HT)
HTA	Inter-regional line and regional distribution	33 KV/ 20 KV/ 15 KV (MT)
BT	Local dispatching, distribution and consumption	400 KV/ 230 KV (BT)

Equivalent Diagram of a Synchronous Generator:

To analyze the power transfer in a system, the representation of each component is necessary to integrate it into a grid. Therefore, it is necessary to build these representations from elementary circuits: resistances, inductors, capacitors, voltage and current sources which will represent the equivalent circuit.

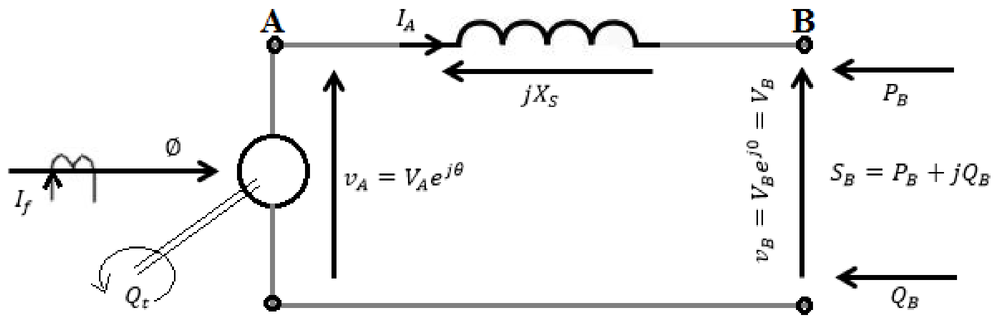


Figure 2 : Equivalent diagram of a synchronous generator.

The electric generator can be reduced to a simple alternative source. The equivalent Thevenin model consists of a sinusoidal electro-magnetic force (f.e.m) in complex form:

$$v_A = V_A \times e^{j\theta} \quad avec \;\; e^{j\theta} = \cos(\theta) + jsin(\theta)$$

And an unknown reactance X_S known as the synchronous reactance. θ, is the angle of the rotor axis to the rotating field and depends on the torque applied to the shaft.

- If, $\theta > 0$, the machine is driven by a motor and is a generator; it then supplies power to the network.
- If, $\theta < 0$, the machine receives power from the network and operates as a motor.

At point B, which corresponds to the input of the grid θ =0 therefore, $v_B = V_B \times e^{j0} = V_B$

Equations Characterizing the Transfer of Power:

It is always interesting to see how power can be supplied to the grid by an alternator. This is possible using complex notation.

The complex apparent power is given by:

$$\underline{S_B} = \underline{V_B} \times \underline{I_B} \tag{1}$$

The current I_B is obtained using the Kirchhoff law:

$$\underline{I_B} = \frac{\underline{V_A} - \underline{V_B}}{\underline{X_S}} \tag{2}$$

By replacing $I_B$by its value in **equation 1**, we obtain:

$$\underline{S_B} = \underline{V_B} \times \underline{I_B} = \underline{V_B} \times \left[\frac{\underline{V_A} - \underline{V_B}}{\underline{X_S}}\right] = V_B \times e^{-j0}\left[\frac{V_A \times e^{-j\theta} - V_B \times e^{-j0}}{jX_S}\right] \quad avec\ \ e^{-j0} = 1$$

$$S_B = V_B\left[\frac{V_A \times e^{-j\theta} - V_B}{jX_S}\right] = V_B\left[\frac{jV_A \times e^{-j\theta} - jV_B}{j^2 X_S}\right]; \quad j^2 = -1$$

$$S_B = V_B\left[\frac{jV_A \times e^{-j\theta} - jV_B}{-X_S}\right] = V_B\left[\frac{jV_B - jV_A \times e^{-j\theta}}{X_S}\right]; \quad e^{-j\theta} = \cos(\theta) - jsin(\theta)$$

$$S_B = V_B\left[\frac{jV_B - jV_A \times (\cos(\theta) - jsin(\theta))}{X_S}\right] = V_B\left[\frac{jV_B - jV_A \times \cos(\theta) + j^2 V_A \times sin(\theta)}{X_S}\right]$$

$$S_B = V_B\left[j\frac{V_B}{X_S} - j\frac{V_A \times \cos(\theta)}{X_S} + j^2\frac{V_A \times \sin(\theta)}{X_S}\right] = V_B\left[j\frac{V_B}{X_S} - j\frac{V_A \times \cos(\theta)}{X_S} - \frac{V_A \times \sin(\theta)}{X_S}\right]$$

$$S_B = j\frac{V^2{}_B}{X_S} - j\frac{V_A.V_B \times \cos(\theta)}{X_S} - \frac{V_A.V_B \times \sin(\theta)}{X_S}$$
$$= -\frac{V_A.V_B \times \sin(\theta)}{X_S} + j\left(\frac{V^2{}_B}{X_S} - \frac{V_A.V_B \times \cos(\theta)}{X_S}\right)$$

$$S_B = -\frac{V_A.V_B \times \sin(\theta)}{X_S} + j\frac{V_B}{X_S}(V_B - V_A \times \cos(\theta)) = P_B + jQ_B$$

With: P_B, the active power at the grid input and, Q_B, the reactive power at the grid input.

From where

$$P_B = -\frac{V_A.V_B \times \sin(\theta)}{X_S} \quad (3)$$
$$Q_B = \frac{V_B}{X_S}(V_B - V_A \times \cos(\theta)) \quad (4)$$

These results were obtained considering the input of grid. If we had considered the active and reactive powers at the output of generator A, we would have obtained:

$$P_A = P_B = \frac{V_A.V_B \times \sin(\theta)}{X_S} \quad (5)$$
And $$Q_A = Q_B = \frac{V_A}{X_S}(V_A - V_B \times \cos(\theta)) \quad (6)$$

Equation 5 confirms the principle of energy conservation in the case of a lossless system, the power supplied by the generator and coming from the mechanical power is equal to the power received by the grid. **Equations 3, 4, 5 and 6** are important because they show the way of transfer's active and reactive powers between the production source and the network.

We can summarize all this by the following equations which apply to all the nodes of a network, each of these nodes being a small part of a system, which is assumed to be operating in a steady state:

$$\begin{aligned} P_{in} - P_{out} - P_{loss} = 0 \Rightarrow \sum P = 0 \\ Q_{in} - Q_{out} - Q_{loss} = 0 \Rightarrow \sum Q = 0 \end{aligned} \quad (7)$$

The terms P_{loss} and Q_{loss} correspond to the consumption of active and reactive power in the transmission lines.

Bayesian Networks

The representation of knowledge and reasoning from these representations has given rise to many models. Probabilistic graphical models, and more specifically the Bayesian Networks (BN), initiated by Judea Pearl in the 1980s, proved to be useful tools for the representation of uncertain knowledge and reasoning from incomplete information, in many sectors such as bioinformatics, risk management, marketing, computer security, transportation, etc.

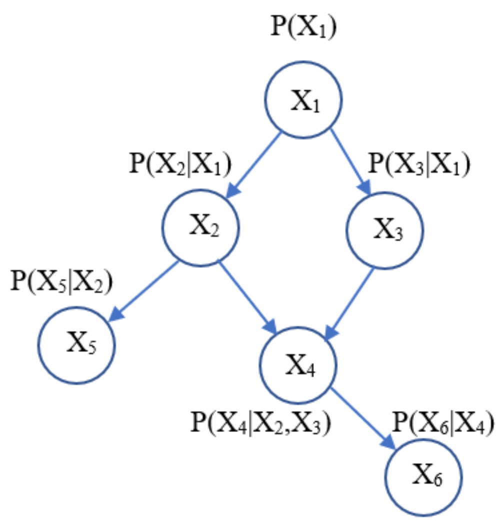


Figure 3 : Example of a Bayesian network

Bayesian networks are a means of combining known (or observed) information with unknown and uncertain (or hidden) information. They enable, thanks to the information provided by experts or a database to establish possible causes for events and thus avoid having to calculate all potential relationships. These are so-called graphical models, where we (with the help of an expert) give the dependencies between events. The structure used for the dependencies is a directed and acyclic graph:

- Directed: connections between possible cause and effect,
- Acyclic: a game cannot (even indirectly) influence its probability,

- Each node contains a table of conditional probabilities.

For each variable, we associate a node and a table of conditional probabilities. For each dependency relation between two variables figure 3.

Dynamic Bayesian Network (DBN)

Dynamic Bayesian Networks (BDN) highlight the relationships of independence between variables, they provide a structured and concise a representation of processes evolving over time.

In particular, BDNs are increasingly used to represent Markov models [14]. They combine the advantages of learning methods, where the models are estimated from observations, with the interests of knowledge-based methods where dependency relationships between variables can be imposed by expert opinion [15]. A BDN, is composed of a series of time slices, where each slice contains a set of variables representing the state of the environment for this time period. Each slice is a Bayesian network (BN), and the same network structure is replicated as time advances [13]. The temporal dynamics of the environment which models the passage from one slice to another is characterized by matrixes of transitions and represented by arcs connecting the different slices to each other. Figure 4 illustrates an example of BDN over 4 time slots.

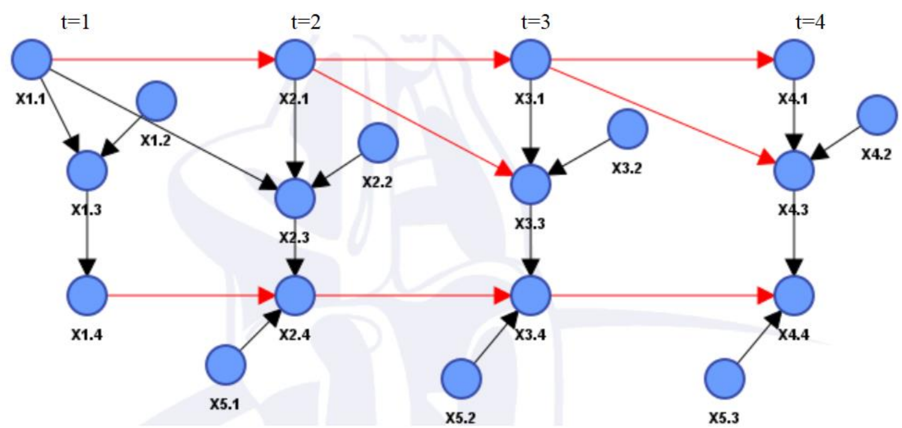


Figure 4 : Example of a dynamic Bayesian Network [13]

A BDN encodes the joint probability distribution of a set of variables $(X_t)_{1\leq t\leq T} = (X_{1,t}, \dots \dots \dots \dots X_{N,T})_{1\leq t\leq T}$ evaluating in time over a sequence of length T. X_t which represents the state of the system at a given time t.

Discretization and Probability Functions

The discretization divides the range of observed values of a variable into intervals and codes these values according to the interval at which they belong. It is based on the choice of the number of intervals defined for each context variable and can be implemented as follows:

- Equidistant intervals, each interval having the same width;
- Quantiles, where each interval tends to have the same number of elements (i.e., pixels); and

- Manually defined intervals, where the user sets the upper and lower limits of each interval.

Discretization has a significant impact on calculated probability functions. These probabilities are calculated by counting pixels according to the dependency relationships defined in the graphical model and the intervals specified in the discretization processes. These conditional relations can follow deterministically (Boolean, arithmetic, ...) or probabilistic (distributions or statistics) relationships.

The formation of the Bayesian Network graphical model and the discretization processes allow the users to add their knowledge about the phenomenon in the model. More, the data set is accurate, and the graphical model, as well as the interval limits during discretization processes, are well defined, the probability based on the data of the calculated functions, represent real probability functions [22].

APPROACH

Introduction

In the literature, Bayesian networks have been applied in several studies, but most of these studies use it for predictive maintenance. (Demet et al., 2006) conducted a study on predictive maintenance using dynamic probabilistic networks [16]. (Dongjin Lee \& Rong Pan, 2017), have predictive maintenance of complex multi-state systems with a reliability structure [17]. Kareem and Owolabi have optimized maintenance planning in the industrial production sector with the Bayesian network [18].

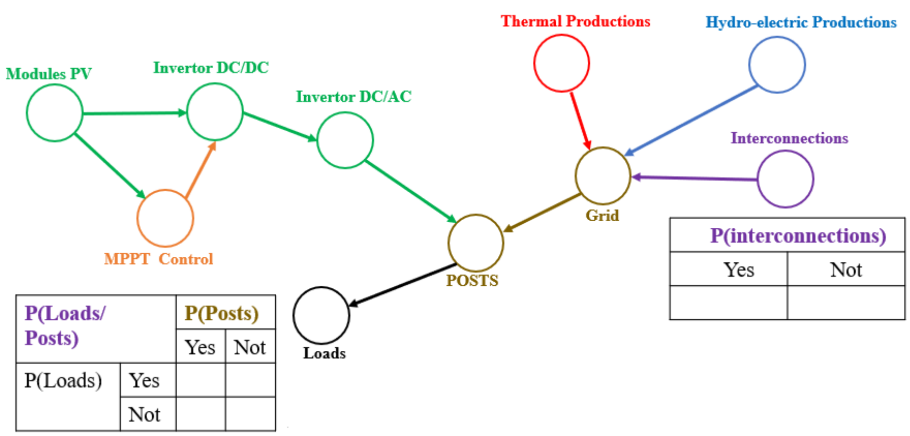


Figure 5 : Example of modeling a PV system connected to the electricity grid

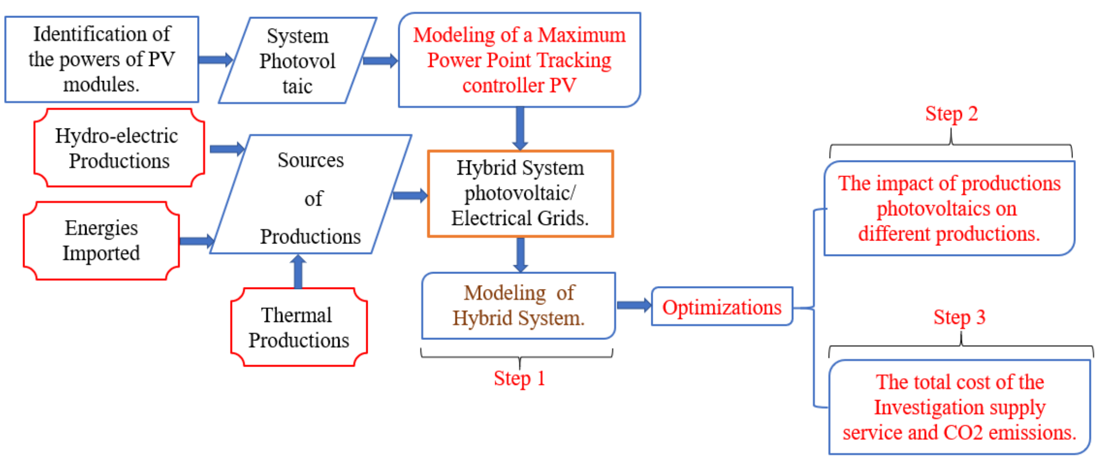
Nevertheless, some studies have used Bayesian networks in the energy sector. We can mention among others, (Fernando Cortez et al., 2015) who studied a cognitive system for the default prognosis in power transformers and (Allan May et al., 2015) have a cost-benefit analysis of offshore wind energy [19], [20]. However, the Bayesian network can be used in several domains to make the right prediction and diagnosis. In our work, we used it in the photovoltaic system connected to the electricity grid, which constitutes our contribution in this context.

The PV generator node represents the photovoltaic source which has for child nodes, control MPPT and converter DC/DC nodes. The MPPT control node controls the DC / DC converter to maintain the PV generator at its maximum output, it is based on information from the PV to drive the DC/DC converter. The DC / AC inverter node whose parent node is the DC / DC converter node, converts the direct current produced by the PV generator into alternating current of the same nature as the grid. The nodes thermal production, hydroelectric production and interconnection are different sources of production that constitute the children of the grid node. The grid node is the sum of its child nodes to have a single point of production. The Station Distribution node has for parent's DC / AC and grid inverter nodes, which interconnects the two sources and distributes it to consumers.

In our approach, we have combined analytical and probabilistic models with the Bayesian network in order to have a real decision-making tool that will allow the dispatching service to make better precision of purchase energy and thermal production. The objective is to reduce the overall costs of production and the emission of greenhouse gases.

Global Approach

Based on the identification of the powers of the PV modules, a photovoltaic system is designed with a maximum power point tracking controller of modules PV. Then, we create a hybrid system with production sources including: hydroelectric power stations, imported energies and thermal power stations. Once the hybrid system photovoltaic/power grid, we model and optimize this system in three steps.



Modeling of the Hybrid System:

Moreover, once these hybrid plants are installed, the problem of managing the variability of solar energy produced according to the availability of the sun poses a major problem. The Bayesian network can combine analytical and probabilistic models in order to have a real decision-support tool that allows the dispatching service to make better purchasing accuracy for energy and thermal production. The different production sources, distribution stations and loads will be modeled by Bayesian networks and then we will develop a timed influence diagram where the distribution will be injected into each node of interest at each moment.

From this Bayesian network, with the help of expert knowledge and the availability of a database, we can act on thermal production which is a source of pollution depending on the availability of alternative photovoltaic sources and the consumer demand. In addition, the dispatcher, can be based on the hours of production of PV sources to reduce daily, monthly or even annual purchases near interconnected suppliers.

For the mathematical modeling, we will use the principle of energy conservation which states that the sum of the energies produced must be equal to the sum of the energies consumed plus the sum of the losses.

For n sources and consumption points we have:

$$\forall\ n \epsilon \mathbb{N} \sum_{i=1}^{n} P_i(Produites) = \sum_{i=1}^{n} P_i(Consommées) + \sum_{i=1}^{n} P_i(Pertes) \quad (8)$$

The **figure 6**, consists the model of our approach which includes the essential elements of an electrical interconnection network, namely: the sources of production, a post of distribution and a point of consumption (load).

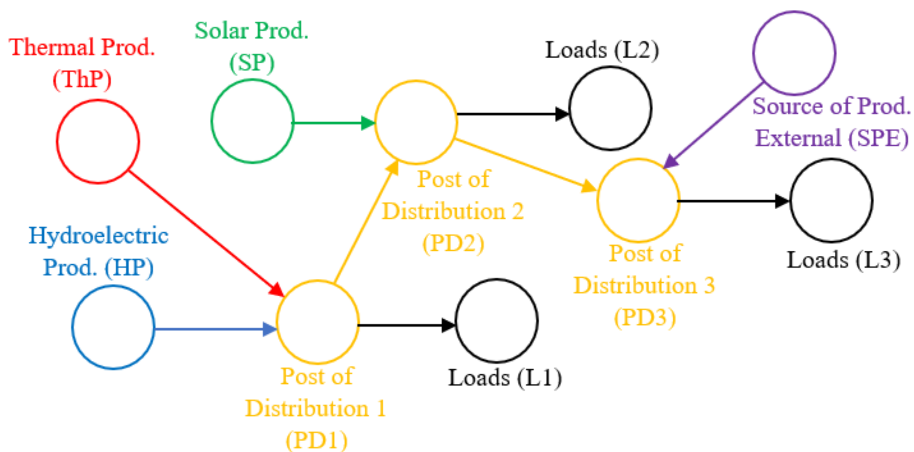


Figure 6 : Electric interconnection network model.

The operating principle is such that at post of distribution 1 (PD1), if thermal production (ThP) and hydroelectric production (HP) are not sufficient to assure the electricity demands of the load 1 (L1), post of distribution 2 (PD2) will support it to compensate the overload. At post of distribution 2, if the electricity demands of the load 2 (L2) and the demand of the post of distribution 1 (PD1) are higher than solar production (SP), then the interconnection network will come in support (IN). We have modeled this operating principle using the following mathematical models:

- At post of distribution 1

$$\begin{cases} if\ PD1 - ThP - HP \geq 0 \Rightarrow PD2 = PD1 - ThP - HP \\ if\ PD1 - ThP - HP < 0 \Rightarrow PD2 = 0 \end{cases} \quad (9)$$

- At post of distribution 2

$$\begin{cases} if\ PD2 + PD1 - SP \geq 0\ \Rightarrow\ IN = PD2 + PD1 - SP \\ if\ \ PD2 + PD1 - SP < 0\ \Rightarrow IN = 0 \end{cases} \quad (10)$$

For the construction of the Bayesian model, we use these mathematical models equation 9 and equation 10 to define a binary state variable of the post of distribution *PD2(t)* and the interconnected network *IN(t)* as follows:

$$\forall\ t: P\big(PD2(t)\big) = P(PD1|ThP, HP)\ et\ P\big(IN(t)\big) = P((PD2 + PD1)|SP) \quad (11)$$

In other words:

$$PD2(t) = \begin{cases} 1\ \ if\ PD1 - ThP - HP \geq 0 \\ 0\ \ else \end{cases} \quad (12)$$

$$IN(t) = \begin{cases} 1\ \ if\ PD2 + PD1 - SP \geq 0 \\ 0\ else \end{cases} \quad (13)$$

The probabilities for all intervals must be equal to 1. In the case of variables that have parent nodes, such as Post Bamako uses the intervals defined for the thermal power station node and those described for the load Bamako node. The user must be expert enough to determine appropriate discrete intervals for each context variable so that all scenarios (a combination of parent intervals and variable) include representative data for probability function calculations. The process of calculating the probability functions of the model is called formation when BN defines the probability functions according to the values observed from the data. By using probability values with possible reasoning, the BNs can deduce based on the evidence (observed data). Indeed, once formed, the BNs can answer the following question: "What is the probability of the presence of a target node (eg, purchase RCI), given the values observed for the variable context (for example, thermal power station and solar).

Influence Diagram:

Bayesian networks, static or dynamic, constitute a decision support tool in the sense that they make it possible to calculate the probability of states according to the available knowledge. This help can, however, be greatly improved by enriching these Bayesian networks with other types of nodes, which are Utility nodes and Decision nodes.

Utility nodes: an influence diagram makes it possible to study the different reactions of a system modeled by the Bayesian Networks according to the actions taken on the system. Thus, thanks to utility nodes, it is possible to compare the performance of a given action (see their combination) on the system and subsequently optimize the various decisions to be made by the decision nodes. The Utility node allows a numeric value to be associated with the states made up of the combination of the different modalities of its parents. These numerical values then represent the quality or the cost of these states. For example, a utility node attached to a maintenance policy can represent the cost.

Decision nodes: like classical nodes, the effect of each of the actions reported by decision nodes is described through the probability tables associated with children. On the other hand, a Decision node does not have a table of probabilities but a table of qualities indicating the policy to be followed. This table of qualities can be completed by expertise, and / or learned automatically. The BayesiaLab tool used in our work effectively integrates the learning function which makes it possible to generate the most favorable decision plan given the indicators (utility nodes) highlighted. More precisely, a reinforcement learning algorithm allows to update the quality of each state / action according to the expected overall utility. For the simulation, in order to optimize the impact of photovoltaic production on the various productions as well as the total cost of investigation of the supply service and the emission of CO2, we need to do some preliminary studies, in particular: analysis of historical data, study of optimization criteria (cost of thermal production, cost of purchased energy) and the environmental assessment.

Analysis of Historical Data:

For this work, we will use the one-year database that can be obtained at the level of the electricity supply service. The data will be summarized in monthly and annual energy produced by each production point.

Study of Optimization Criteria:

Cost of Thermal Production:

The simulation model that will follow searches for the optimal solution on the basis of the costs that the section below details. For calculations of thermal production costs, knowing the specific monthly consumption (in liters / kWh) and annual thermal production (in kWh) we can calculate the fuel consumption of the generators by multiplying them. Once the consumption in liters by the generators is known, we calculate:

- Annual cost of diesel: C_{ad} This cost is equal to the annual diesel consumption multiplied by the price of a liter of diesel;
- Annual maintenance cost of power plants: C_{maint} This cost constitutes the maintenance of the various components of the power plant.

The operating cost will be:

$$C_{exp} = C_{ad} + C_{maint}$$

Cost of Purchased Energy:

For calculations of the costs of energy purchased by the electricity supply service, we can use the information obtained at the service level regarding the price per kWh that the service buys imported energy. Knowing the annual energies purchased, we will be able to obtain the costs of the energies purchased by multiplying these annual energies by their unit prices.

Environmental Assessment:

The environmental assessment consists in carrying out a study on the quantities of carbon dioxide (CO2) emitted by the various sources of production, which is an important factor of global warming.

The emissions associated with the production and combustion of one tonne of coal, oil or natural gas are known. On the other hand, as regards electricity, the subject is more complex and supposes an adapted methodology to avoid fundamental errors in the analysis according to a study of balance of energies. Indeed, the comparison of emissions from energy emissions is essential, because these are the major elements on the basis of which we must define the energy challenges and monitor their implementation by the actors concerned. Consumer use of electricity does not cause CO2 emissions at the point of use. However, the fuels used to produce electricity as well as the construction and maintenance of production plants, transmission and distribution networks are the source of emissions.

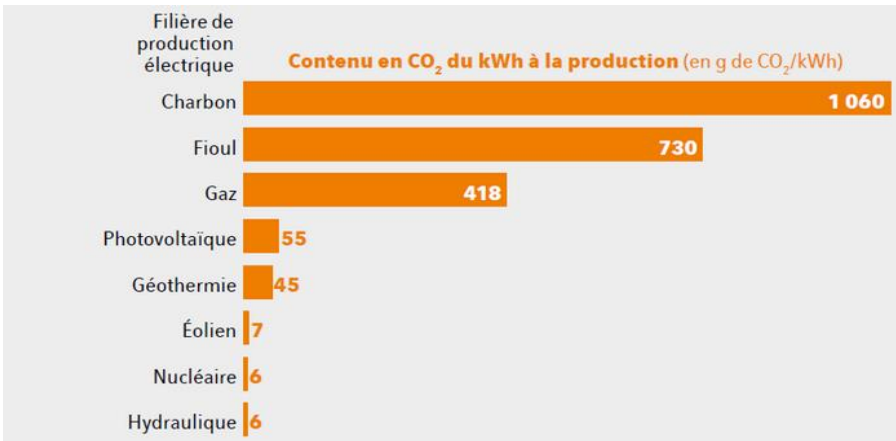


Figure 7 : CO2 content per kWh during production according to the sources

Source: Ademe carbon base. Note: These sources include direct and indirect emissions to production balance of energies.

The carbon content (or emission factor) of a kWh of energy corresponds to the quantity of CO2 emitted, over a specified time interval and over a perimeter given by one kWh of electrical energy made available to a consumer. We know the CO2 content in production, whether it is a power plant or a production park. Thus, hydraulics, nuclear, solar and wind do not generate direct CO2 emissions to production and very few indirect emissions (construction of power plants in particular); gas-fired power plants emit around 400 g/kWh of CO2 and coal-fired power plants around 1,000 g/kWh figure 7.

CASE STUDY

Our approach is applied to the Mali energy interconnection network (EDM-Sa). This network is shown in figure \ref{fig6}. Electricity demand is assured by EDM's specific hydroelectric power stations, thermal power stations and largely purchased from a neighboring country Ivory Coast, and Manantali's production. We have connected three solar power plants of 30 MW at three posts of electricity distribution (Kayes, Kita and Fana).

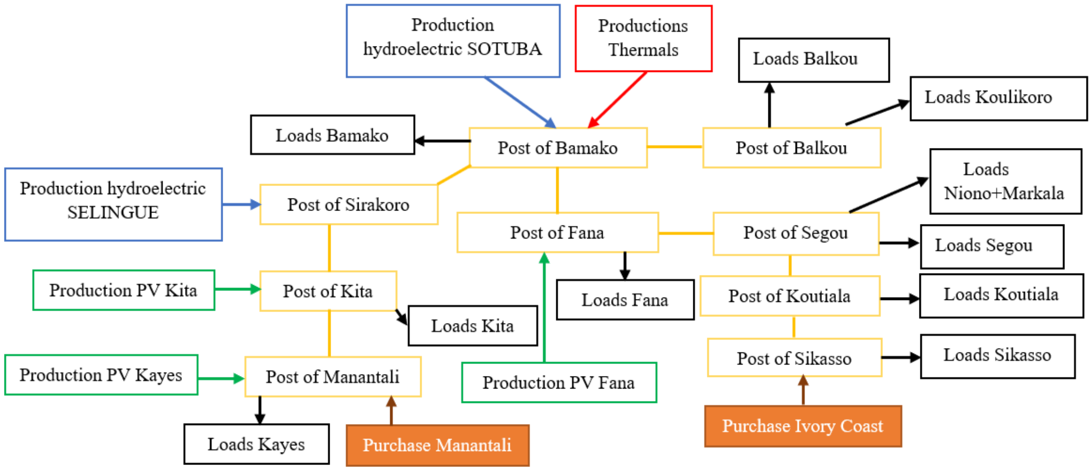


Figure 8 : Mali electricity supply interconnection network.

This interconnection network ensures the supply of electricity to four (4) regions and these big cities and the capital of Mali. It includes different sources of production including points of purchase (Ivory Coast and Manantali), distribution posts and consumption points. EDM-sa's own hydroelectric production sources are coded in blue, thermal production in red, photovoltaic production in green and purchasing points in purple. The distribution posts are coded in yellow and the consumption points are in black.

Analysis of Data from Data History

For this work, we have used the data for a period of a year collected at the level of the National Order Center, which is the service of regulation of the EDM.

Table 2 : Annual data for the various energy productions in Mali.

Mois	**SELINGUE (MWh)**	**SOTUBA (MWh)**	**Thermal (MWh)**	**Manantali (MWh)**	**Ivory Coast (MWh)**
January	13 579	3 400,49	13451,86	48496,05	25 648
February	12 459	2 989,87	32178,05	49778,31	23 031
March	15 629	3 214,04	56680,11	61523,36	17 129
April	16 762,77	2 968,32	71825,62	67959,39	16 433
Mai	16 065	3 247,83	76790,88	70571,91	17 070
June	10 981	2 573,41	78954,24	63836,34	13 902
July	8 215	2 442,03	67240,86	69708,19	12 703
August	15 643	2 185,01	43814,06	51921,07	23 141
September	16 448	1 606,60	33089,22	51440,86	26 661
October	17 072	1 715,26	45692,29	58242,60	27 183
November	12 844	2 152,46	35076,50	58514,75	18 361
December	14 031,93	3 235,33	35045,25	45825,56	15 784
Annuelle	**169729,70**	**31730,65**	**589838,94**	**697818,39**	**237046**

In table 2, we have summarized the annual data that the agents of the National Order Center gave us with the Excel tool. The data is summarized in monthly energies produced by each production point. The total energy produced is 1726.164 GWh/year, of which 237.046

GWh/year purchased by the neighboring country Ivory Coast, i.e. 14% of total production and 697.818 GWh/year purchased on the Manantali interconnected network, i.e. 40% of total production. The total energy purchased by Mali's electricity supply service was 934.864 GWh / year (75% for Manantali and 25% for Ivory Coast). Thermal production was 589.839 GWh/year which is 34% of total production and the hydroelectric production specific to EDM Sélingué and Sotuba were respectively 169.73 GWh/year and 31.731 GWh/year, i.e. 10% and 2% of production total figure \ref{fig8}. From the analysis of these data, we noted that the electricity supply service of Mali bought 54% against 46% of these own sources of production. Among these 46%, thermal production is 34% and 12% hydroelectric production which is insignificant.

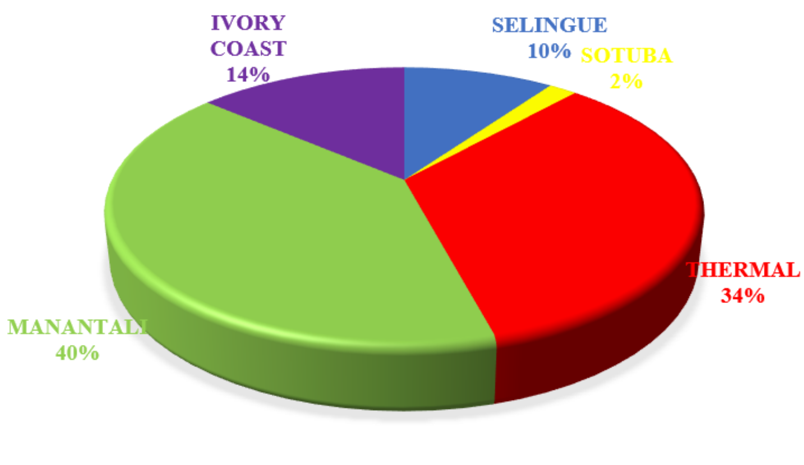


Figure 9 : Distribution of annual productions.

Cost Study

Cost of Thermal Production:

For the calculations of the costs of thermal production, we have based ourselves on the specific monthly consumption. These data are obtained by EDM agents (source EDM-sa) and we had an average consumption of 0.293 l/kWh.

- Fuel consumption of the Generators

Knowing the specific consumption in diesel which is 0.293 liters/kWh and the annual thermal productions which is 589,838.94 MWh in table 2, we can calculate the consumption in fuel (in liters).

Table 3 : Summary of fuel consumption calculations.

Designation	Specific consumption in fuel (liter/kWh))	Annual energy produced (MWh	Annual consumption in fuel (liter)
Diesel generators	0,293	589 838,94	172 822 809,42

Remember that 1MWh is equal to 1000 kWh. Table 3 summarizes these calculations for us. We noted consumption of 172,822,809.42 liters by generators.

- Annual cost of diesel: C_{ag} (FCFA)

This cost is equal to the annual consumption of diesel multiplied by the price of a liter of fuel knowing that: 1 liter of diesel is about 500FCFA (0.762 € euro) in this period in Mali.

$$C_{ag} = 172\,822\,809{,}42 \times 500$$
$$C_{ag} = 86\,411\,405\,124\ FCFA$$

- Annual maintenance cost of power plants: C_{maint} (FCFA)

This cost constitutes the maintenance of the various components of the power plant, which we have approximately estimated at 5% of the cost of the annual consumption of the power plants per year.

$$C_{maint} = 86\,411\,405\,124 \times 5\% = 4\,320\,570\,236\ FCFA$$

The operating cost will be:

$$C_{exp} = C_{ag} + C_{maint}$$
$$C_{exp} = (86\,411\,405\,124\ + 4\,320\,570\,236)\ FCFA$$
$$\boldsymbol{C_{exp}} = \mathbf{90\,731\,975\,360\ FCFA}$$

The annual operating cost of thermal production was 90,731,975,360 FCFA (138,320,004.75 euro).

Cost of Energy Purchased:
For the calculations of the costs of energy purchased by the Mali electricity supply service, we have used the information below obtained near EDM's agents.

According to this information, the EDM buys a kWh at 50 FCFA from Manantali and 80 FCFA at the level of Ivory Coast. Knowing the annual energies purchased at the levels of Manantali and Ivory Coast which are respectively 697,818.39 MWh and 237,046 MWh table 2, we can obtain the costs of the energies purchased by multiplying these annual energies by their respective unit prices.

- Annual cost purchased at the level of Manantali

$$C_{Achat\_M} = 697\,818{,}39 \times 1000 \times 50 = 34\,890\,919\,500\ FCFA$$

- Annual cost purchased at the level of Ivory Coast

$$C_{Achat\_C} = 237\,046 \times 1000 \times 80 = 18\,963\,680\,000\ FCFA$$

The overall cost of the energy purchased is:

$$C_{Achat\_Energies} = C_{Achat\_M} + C_{Achat\_C} = (34\,890\,919\,500 + 18\,963\,680\,000)\ FCFA$$
$$\boldsymbol{C_{Achat\_Energies} = 53\,854\,599\,000\ FCFA}$$

The annual energy purchased was 53,854,599,000 FCFA (82,100,806.913 euros).

Table 4 : Costs of production of thermal energies and imported energies.

Productions	Annual Energy (MWh) (FCFA)	Price per MWh	Cost of Productions (FCFA)	Cost of Maintenance (FCFA)	Total production production (FCFA)
Thermal	589 838,94	146 500	86 411 405 124	4 320 570 236	90 731 975 360
Manantali	697 818,39	50 000	34 890 919 500	-	34 890 919 500
Ivory Coast	237 046	80 000	18 963 680 000	-	18 963 680 000
Total					**144 587 000 000**

Table 4 summarizes the production costs of thermal energies and imported energies. By analyzing this table, we note that roughly 90.731 billion FCFA (138.320 million euros) were invested for thermal production and 53.854 billion FCFA (82.100 million euros) for the energy purchased, an expenditure estimated at 144.587 billion FCFA (172.831 million euros) per year. Which is huge for a country like Mali. In table 4, we have not treated the productions of Selingué and Sotuba which are sources of hydroelectric production of the EDM and of which we considered them permanent in our case of simulation.

Environmental Assessment

For our case study, the thermal power plants use fuel oil as a fuel source so their emission rates are 730 g/kWh and on this basis, we can calculate the amount of CO2 emitted by the sources of thermal energy production in Mali. This rate will be multiplied by the annual energy produced by thermal production, which is 589,838.94 MWh table 2. According to calculations, the thermal power plants emitted 430,582,428 kg of CO2 for a year. The emission rate for hydroelectric is 6g/kWh (figure 7) and summing all the hydroelectric generation in our system, we will have 1,136,325 GWh/year. According to calculations, the emissions from hydroelectric production are 6,817,950 kg/year. The total CO2 emission is 437,400,378 kg/year.

Construction of the Bayesian Model

The Bayesian network in figure 10 is the typical model of our interconnection network. The transition to the Bayesian network is done so that at the Bamako’s distribution post, if thermal production and own hydroelectric power stations are not sufficient to cover the loads of the city of Bamako, the post of the city of Fana will come to support to compensate for the overload. At the Fana post, if the load of the city of Fana and the demand from the Bamako post are higher than the available solar production of Fana, then the Segou post will support. Sikasso's post works the same way as Fana. If no PV and thermal production is available, all the charges will be supplied by own hydroelectric production and the Ivory Coast and Manantali interconnection networks. The assumption is that the availability of thermal production and solar energy should reduce purchases at the levels of Manantali and Ivory Coast.

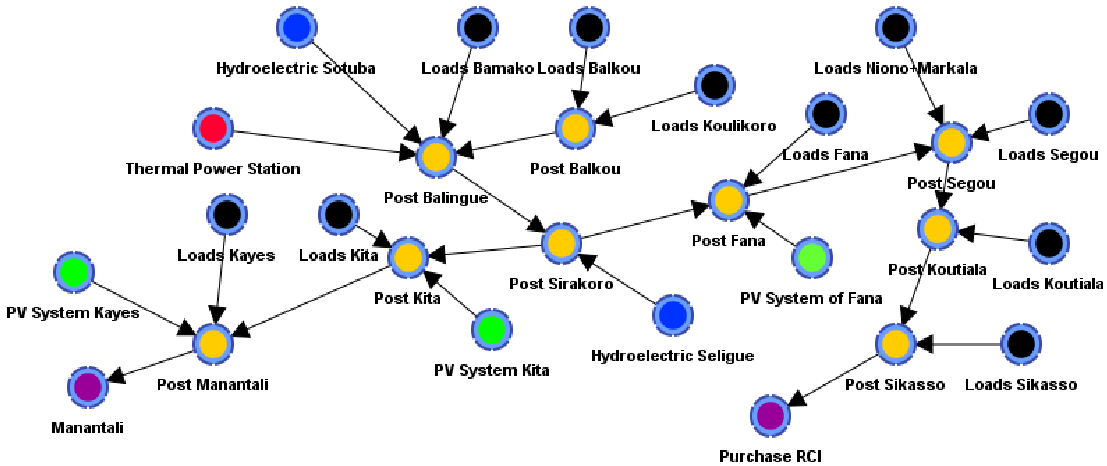


Figure 10 : Bayesian model of the Mali interconnection network.

In our case study, the nodes of the solar productions each having a production capacity of 30 MW which don't have parental nodes were discretized using ten continuous intervals equidistant according to probabilistic relationships. Their probability distributions are made on the basis of solar production data from the different sites. The nodes of the different loads are discretized on continuous intervals with a probabilistic distribution. The nodes of the posts followed deterministic relations with conditional equations and were discretized on equidistant intervals. The Manantali and Ivory Coast purchasing nodes, which can take on all the charges in the case of unavailability of other sources, are discretized over equidistant intervals and follow probabilistic relationships. The probabilities for all intervals must be equal to 1.

For the work, we relied on the one-year database collected at the level of the electricity distribution structure in Mali.

Declination in Influence Diagram

In this part we have added additional nodes (see figure 11), in particular eight (8) decision nodes corresponding to the sources of energy production of our model which will allow dispatchers to decide at what time it is necessary to activate or not the photovoltaic systems, put in power plants or not and buy or not energy at Manantali and Ivory Coast.

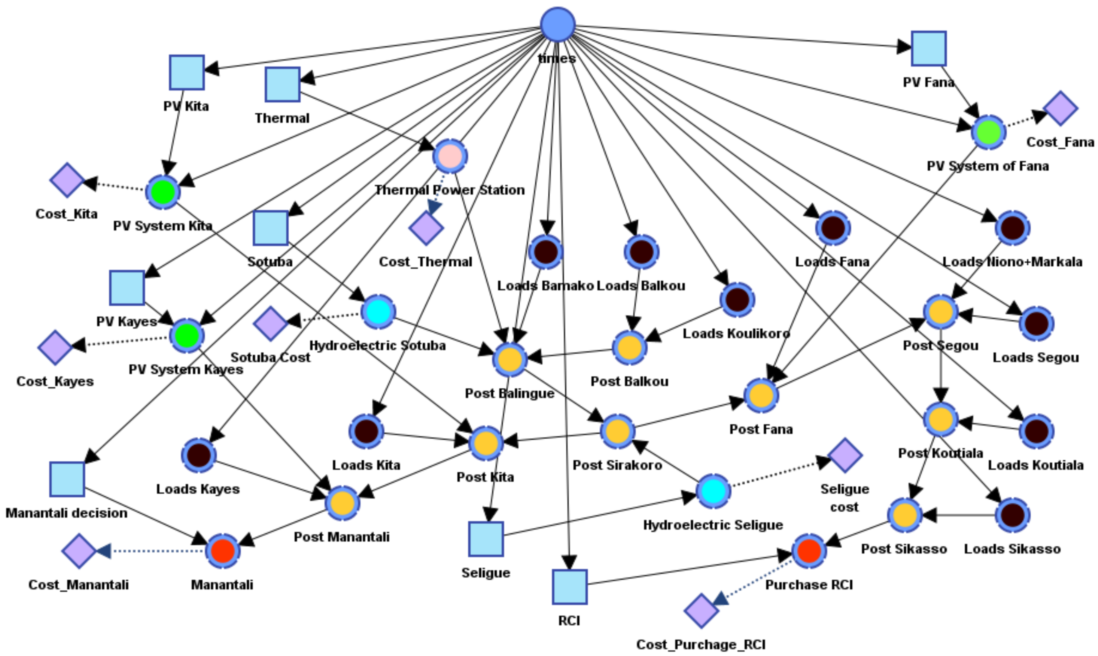


Figure 11 : Dynamic Bayesian model of the Mali interconnection network.

In our model, the decision nodes are influenced by the state at time t which will influence or determine the state of this system at time (t + 1). In addition, we have eight (8) cost nodes which will allow us to enter the production costs of each production source. For the training these cost nodes, we used the production cost data for thermal energies and imported energies in table \ref{tb3}. These cost nodes are performance indicators for the evaluation and simulation of the optimal choice.

SIMULATION

For the simulation, we injected the 8760 data from each production system (equivalent to one year of measurement) into our model. The production costs of the SELINGUE and SOTUBA production systems have not been examined, since they are EDM's own hydroelectric productions and which have negligible ecological impacts compared to thermal productions.

Table 5 : Les différentes polluants pour la simulation sans les systèmes PV.

Polluants	**Thermal (kg/an)**	**Energy purchased (kg/an)**	**Others productions (kg/an)**
Carbon dioxide	430 615 887	5 749 096	22 138 542
Carbon monoxide	2 646 817	0	207 192
Unburned oil	111 643	0	12 896
Particles	16 041	0	1 256
Sulfur dioxide	1 610 007	2 625 421	508 146
Nitrogen oxide	2 486 404	1 283 965	2 954 619

Table 5 illustrates the different emissions of greenhouse gases using thermal productions and purchased energies which have ecological impacts.

The Impact of Photovoltaic Productions on The Energies Purchased

In this part, we have made a simulation using PV systems. The objective is to see how solar productions can help to reduce the energy purchased with the neighboring country and Manantali. We have summarized the simulation results in Table 6. We recall, that we used a PV system of 30MW at the level of three cities on the electricity supply network of Mali.

Table 6 : The different annual energies produced and their production costs with PV systems by playing on the energies purchased.

Power stations	Production (kWh/an)	Percentage (%)	Production costs (FCFA)
Manantali	602 518 035,75	34,65	34 906 761 549
Ivory Coast	200 839 345,25	11,55	11 635 587 183
SELINGUE	171 724 700	9,80	-
SOTUBA	31 196 600	1,78	-
THERMAL	589 840 573	33,50	89 469 188 025
System PV KITA	49 721 762	2,84	-
System PV KAYES	48 852 313	2,80	-
System PV FANA	53 796 455	3,08	-
Total	**1 748 489 783**	**100**	**136 554 984 868**

By comparing tables 6 and 2, we will see that PV systems have contributed to reducing the total purchased energy from 934.864 GWh/year to 803.357 GWh/year, a difference of 152.323 GWh/year. This reduced the total cost of production from 145.76 billion FCFA to 136.555 billion FCFA per year table 6, a gain of 9.205 billion FCFA.

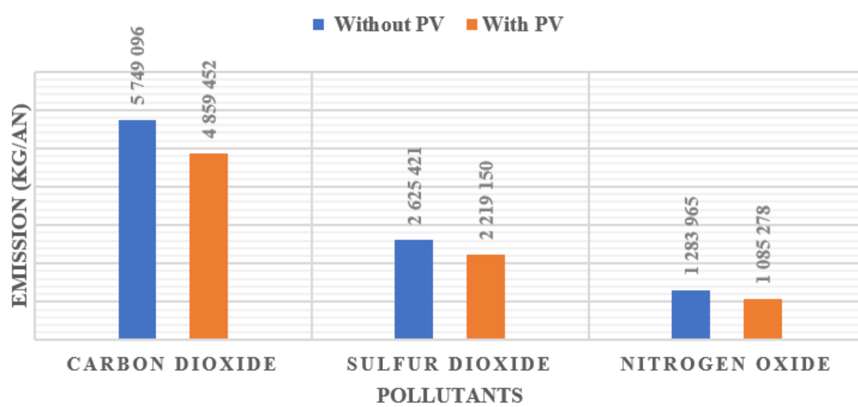


Figure 12 : Greenhouse gas emissions before and after the use of PV systems.

In figure 12, we can see a reduction in greenhouse gas emissions, which are still significant, but these values are only the emissions from the sources of production of the energy purchased. The total CO2 emitted has been reduced from 458,503,525 kg/year to 455,358,714 kg/year.

The Total Cost of The Investigation Supply Service and CO_2 Emissions

Here, we have made a simulation using PV systems without playing on any of the productions (thermal and purchased energy).

The objective is to see if it would be beneficial to distribute the energies produced by PV systems between the energies purchased and thermal productions.

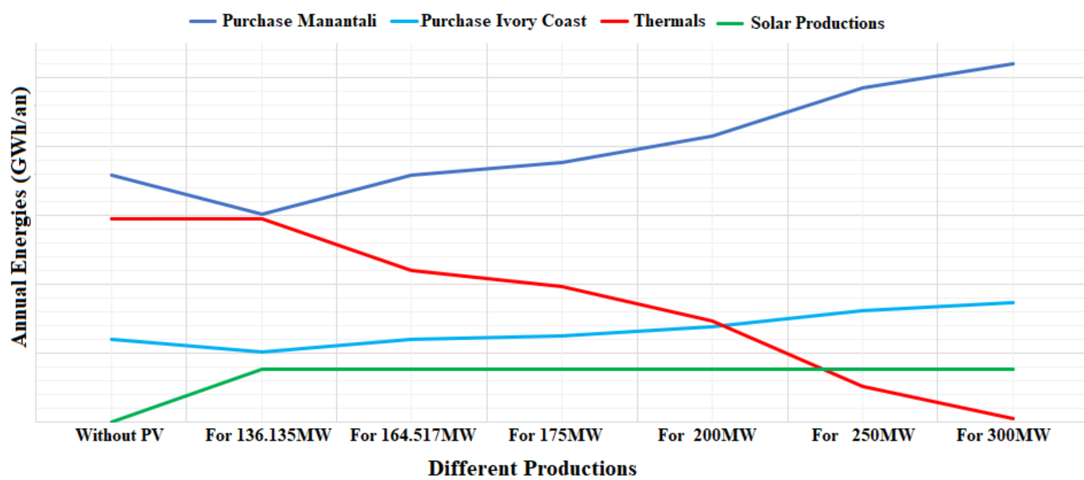


Figure 13 : The trend of different productions according to forecasts.

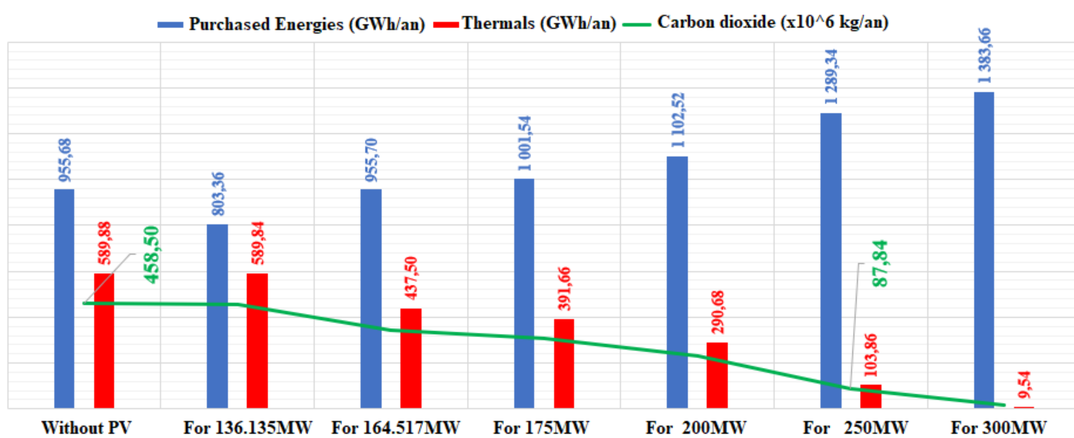


Figure 14 : The amount of carbon dioxide emitted for the different forecasts.

Another important objective of this part is to get an idea of how many MW per day the supply service must buy to stay in the previous scenarios. For the simulation, we fixed the value of energy purchases and increase it gradually so as to balance the distribution of solar productions. For the first scenario, the service must buy around 136.135 MW per day. For the second scenario, the service must plan to buy 164.157 MW per day to remain in this scenario.
After having found the conditions of purchase for the two scenarios, we proceeded to series of simulation by increasing the powers to buy. These simulations have the objective of playing on the operating cost, we have analyzed the forecast cases of 175MW, 200MW, 250MW and 300MW in figures 13, 14 and 15. Figure 13 illustrates the trend of different productions depending on the power demand. We note that the more the forecast of energy purchases increases the more the production of thermal energies decreases. Thermal production becomes lower than solar production when we plan to buy 250MW/day. For a purchase forecast of 300MW/day, thermal production is almost insignificant figure 13.

Figure 14 summarizes the emission balance for carbon dioxide (CO2), which is the most polluting element in greenhouse gases. We observe that the CO2 emissions are proportional to the thermal productions and inversely proportional to the purchase of energies.

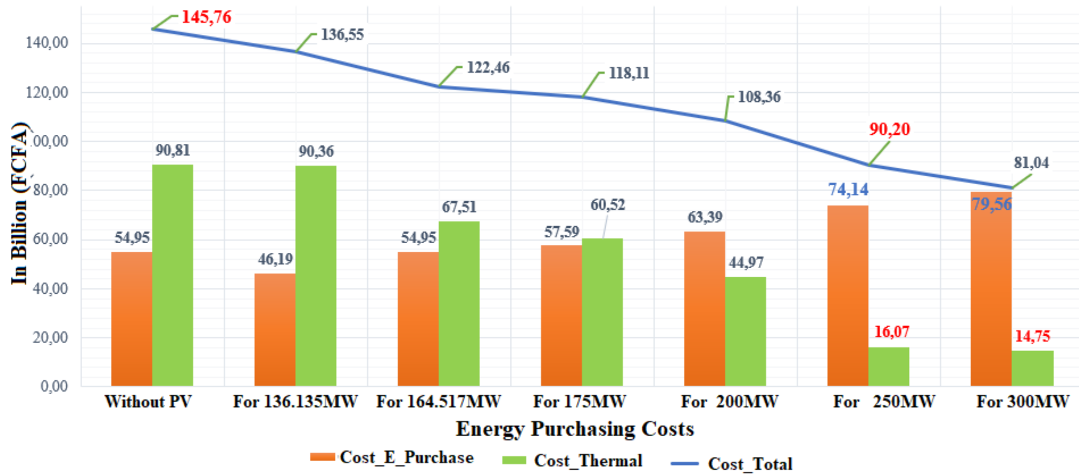


Figure 15 : The annual production costs of the different productions.

For a purchase forecast of 136,135MW/d, there was an annual energy purchase of 803.36 GWh/year and thermal production of 589.84 GWh/year resulting in an emission of 458,500,000 kg/year. This emission decreased to 87,840,000 kg/year and 15,660,000 kg/year for a purchase forecast of 250MW and 300MW corresponding respectively to an annual thermal production of 103.86 GWh/year and 9.54 GWh/year.

Figure 15 shows the costs of thermal productions, the costs of energies purchased and the total cost of using these energy sources by the electricity supply service in Mali. It shows that the use of PV systems has helped to reduce production costs.

It can be clearly observed that by increasing the forecast to buy more, the total cost of use is considerably reduced. The forecast to buy 136.135 MW/day is the most expensive at around 136.55 billion FCFA for a cost of thermal productions of 90.36 billion and a cost of energy to buy of 46.19 billion. By increasing the forecast to buy, the cost of thermal production decreases by reducing the total cost of use. This total cost will be reduced to 90.2 billion and 80.035 billion FCFA for a forecast of 250MW and 300MW per day respectively. Through the analysis of figures 14 and 15, we note that for the forecast to buy 300MW/day, thermal productions to decrease from 103.86 GWh/year to 9.54 GWh/year figure 14 but the cost of thermal production has only decreased from 16 billion to 14.75 billion FCFA figure 15, the ratio is really low. So, it would not be desirable to exceed a 250 MW/day purchase forecast. We also notice that, thermal productions that are expensive and not recommended for supplier service.

DISCUSSION AND CONCLUSION

The Mali electricity supply service called Mali energy (EDM-sa) includes own production systems constituting hydroelectric power stations and thermal power stations, production systems Manantali and the interconnection network Ivory Coast whose service buys energies.

The total energy produced during 2018 was 1,726,164 GWh/year, of which 237,046 GWh / year was purchased with neighboring country Ivory Coast, i.e. 14% of total production and 697,818 GWh/year purchased on the interconnected grid of Manantali, 40% of the total production. The total energy purchased by Mali's electricity supply service was 934,864 GWh/year (75% for Manantali and 25% for Ivory Coast). Thermal production was 589,839 GWh/year or 34% of total production and the hydroelectric production specific to EDM Selingue and Sotuba were respectively 169.73 GWh/year and 31,731 GWh/year, i.e. 10% and 2% of production total figure 9. We have used Bayesian Networks to model our case study. The goal was to allow the dispatching service to have a decision support tool that will allow the dispatching service to make better purchasing precision for energy and thermal productions. For that we have combined analytical and probabilistic models with the Bayesian network.

A first simulation was made without the photovoltaic systems to make the economic and ecological assessment of the year. CO2 emissions were 458,503,525 kg/year for thermal production and the cost of thermal production was approximately 90.81 billion FCFA, the energy purchased with Manantali about 41.21 billion and the energy purchased with the Coast Ivory Coast was about 13.74 billion with a total production cost of 145.76 billion FCFA. Then we have done a simulation with photovoltaic systems by considering three scenario cases. The first scenario was to maintain thermal production as we have found in order to see the impact of solar production on the energy purchased. The simulation of this scenario does not bring enough effect, the total cost of productions only reduced from 145.76 billion FCFA to 136.55 billion FCFA per year table 4 and 6, a gain of 9.21 billion FCFA and CO2 emissions have been reduced from 458,503,525 kg/year to 455,358,714 kg/year.

The second scenario was to play simultaneously on thermal productions and purchased energies in order to reduce the investigation cost of the electricity supply service in Mali using PV. In this part, we have increased the forecast of the energies to buy and observed the economic and ecological effects. The results of the simulation showed us that by increasing the purchase forecast, the total investigation cost decreases as well as the CO2 emissions figures 13 and 14. This total cost can be reduced from 145.76 billion FCFA initially to 90.2 billion and 80.035 billion FCFA for a forecast of 250MW and 300MW per day respectively and CO2 emissions can be reduced up to 87,840,000 kg/year and 15,660,000 kg/year for these forecasts. An analysis of figures 14 and 15 knew us that the forecast to buy 300MW/day is not beneficial. Thermal productions decrease from 103.86 GWh/year to 9,54 GWh/year figure 14 but the cost of thermal productions have only decreased from 16 billion to 14.75 billion FCFA figure 15, so the ratio is low. In this case, it would be desirable not to exceed a purchase forecast of 250MW/day. In conclusion, thermal productions are the costliest economically and ecologically.

Although, the lower production of the thermal power plant, CO2 emission and others polluting factors stay yet important, 87,840,000 kg/yr for a purchase forecast of 250 MW/day. However, it's possible to reduce this CO2 emission at 15,660,000 kg/year with a forecast of 300MW but this one is not beneficial according to an analysis of figures 14 and 15. Thus, in perspective, we can see if it will be cheaper to use another alternative renewable source non-polluting such as wind energy or such as Biomass instead of thermal production.

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