Energy Resources Intelligent Management using on line real-time simulation: a decision support tool for sustainable manufacturing


## ABSTRACT

At a historic time when the eco-sustainability of industrial manufacturing is considered one of the cornerstones of relations between people and the environment, the use of energy from Renewable Energy Sources (RES) has become a fundamental element of this new vision. After years of vain attempts to hammer out an agreement to significantly reduce $CO_2$ emissions produced by the burning of fossil fuels, a binding global accord was finally reached (Paris December 2015 - New York April 2016).

As we know, however, some of the most commonly-used RES, such as solar or wind, present the problem of discontinuity in energy production due to the variability of weather and climatic conditions. For this reason, the authors thought it appropriate to study a new methodology capable of marrying industrial users' instantaneous need for energy with the production capacity of Renewable Energy Sources, supplemented, when necessary, by energy created through self-production and possibly acquired from third-party suppliers. All of this in order to minimize $CO_2$ emissions and company energy costs.

Given the massive presence of stochastic and sometimes aleatory elements, for the proposed energy management model we have used both Monte Carlo simulation and on-line real-time Discrete Event Simulation (DES), as well as appropriate predictive algorithms. A test conducted on a tannery located in southern Italy, equipped with a 700 KWp photovoltaic installation, showed extremely interesting results, both economically and environmentally. In particular the application of the model permitted an annual savings of several hundreds of thousands of euros in energy costs and a comparable parallel reduction of $CO_2$ emissions. The systematic use of the proposed approach, gradually expanded to other manufacturing sectors, could result in very consistent benefits for the entire industrial system.



Keywords: Sustainable Manufacturing, Renewable Energy, On-line real-time Discrete Event Simulation, Energy Management; Energy Saving; CO2 reduction.


## 1 Introduction and literary review

Since the early 2000s, the concept of Sustainable Manufacturing has had an increasing presence in the industrial field. To summarize extremely briefly, the principal objective is to establish a relationship between manufacturing and the environment, with greater attention to protecting the latter.

The idea of sustainability applies and extends to each phase of the industrial manufacturing cycle:

- in product design: possibly making use of recyclable and non-polluting materials;
- in manufacturing: seeking to minimize manufacturing waste and the use of energy from traditional sources and the consequent $CO_2$ emissions;
- in distribution: reducing as much as possible ground transportation and the product's carbon footprint.

A significant contribution for sustainability is made by the correct management of energy, particularly electric power. A complete analysis of the importance of energy management in manufacturing has been recently presented in a review article based on 365 papers published from 1995 to 2015. The authors investigated six main lines of researh related to energy management in this specific context of study [1]. The term "sustainable", when applied to the use of energy, is evoked, on the one hand, in the search for less consumption per unit produced, and on the other hand, in the growing use of self-production through Renewable Energy Sources (RES). "Cleaner Energy for cleaner production" was the leit motiv of the 17th conference "Process Integration, Modelling and Optimization for Energy Saving and Pollution Reduction-PRESS" which aim was to share with the scientific community ideas and technologies that can be used in the real word. Modelling, Simulation and Optimization were the main topics of this conference [2]. However, in the face of the above, there is a significant problem caused by randomness in the volumes of production generated by most RES, whose behavior is predictable only with margins of uncertainty, which are not always trivial. This makes their use problematic in cases where there are continuous consumption demands according to pre-set schedules, as with industrial applications. Until effective storage systems become available, it will always be necessary to supplement discontinuous RES sources (sun and wind, for example) with traditional sources to ensure continuity in energy supply during the hours in which RES production is absent. A focus on sustainability therefore requires the identification of an integrated management model that privileges, where possible, the self-production of RES and minimization of the use of traditional sources. Some authors consider the storage of energy supplied by RES, that at times exceed the demand, as a way to reduce the mismatch between the supplied energy and the forecasted production, due to forecasting errors, using the Stochastic Approximation Average technique [3]. Other authors attempted to reduce both the energy consumption costs and $CO_2$ emission by predicting the energy consumption using predictive methodologies as the Methods-Energy Measurement [4].

After an accurate analysis of the scientific literature, the authors note the lack of methodologies with the objectives presented in this paper, that is, an energy management strategy that allows the simultaneous minimization of $CO_2$ emissions and costs of production, acting, under stochastic conditions, both from the perspective of energy consumption and production by RES and traditional sources.

In fact, some authors approach the problem only from the perspective of predicting energy demand [5-8] while many others only from the perspective of predicting energy availability from RES sources [9-15]. With regard to the use of DES for the purpose of energy savings and optimization of consumption, the authors found some interesting contributions. Ghani et al. use DES for the real-time evaluation of energy demand in the automotive industry in the redesigning phase of the manufacturing process in order to optimize the sizing of the production line with a view toward energy savings [16].

Kouki et al. developed a framework called ERDES (Energy-Related Discrete Event Simulation), which again uses DES for the purpose of predicting future energy consumption at various times of the day in order to test different scheduling scenarios for manufacturing activities and, consequently, minimizing energy costs [17].

Both contributions, though offering interesting insights, approach the problem only from the perspective of optimization of consumption and not production of RES energy.

Some authors have recently proposed a real time method of energy control in manufacturing systems. Their aim is to have an increase of production of energy by RES on site. They act in stochastic regime using also DES but their methodology, according to the authors themselves, shall be improved because there is no fit with the paradigm of Lean Manufacturing [18].

In order to obtain effective and efficient management of RES, predictive models for both the industrial energy demand and the production capacity of RES (in relation to the predicted weather and climactic patterns) are required. The objective of the proposed study is to provide Energy Managers in manufacturing environments with a support tool that, using the potentialities of Discrete Event Simulation (both on-line and on-line real-time) and the Monte Carlo simulation , supplemented by a special predictive algorithm, allows optimization of the energy supplying mix (self-production from renewable and not renewable sources and/or purchase on the electricity market).

Through this approach, as we will see below, both the economic impact, in terms of energy procurement costs, and the environmental impact, expressed in terms of reduction of $CO_2$ emissions, can be significantly reduced. This is in full accord both with the Sustainable Manufacturing

Compared to the models found in literature the methodology proposed by the authors is able to optimize both the cost of energy and the CO2 emissions without affecting the scheduling of production. It is the model that fits to the reality on the basis of the changed operating or atmospheric conditions and not vice versa.

Another important feature is, as demonstrated in the test case described in the paper, the relative ease of application of the proposed methodology. To apply the methodology no specific knowledge on the logic and the statistical tecniques underlying the model are required. To manage optimally energy sources is sufficient interpret the results provided by the model. The authors point out that, unlike other studies, the proposed methodology takes into account the self-production through cogenerative microturbine and the purchase or sale of energy produced to the grid (in defect or in excess , respectively), in order to preserve the economic sustainability of the operation.

## 2 Methods: the ERIM-P and ERIM-RT models

In dealing with the problem of the supplemented and optimal use of energy produced by RES in manufacturing, the authors, taking some DES previous studies [19-20] as a jumping-off point, propose a management approach based on two steps, supported by two respective models called ERIM-P (Energy Resources Intelligent Management-Predictor) and ERIM-RT (Energy Resources Intelligent Management-Real Time).

The purpose of ERIM-P is to develop, 24 hours in advance, two types of predictions:

1) the hourly electrical energy requirement of the manufacturing plant based on a production plan created for the next day, but keeping in mind the stochastic events present in the system (breakdowns, stoppages, missed appointments, availability of materials, variability of processing and set up times, etc.)
2) the quantity of possible self-production of RES energy based on weather predictions for the next day.

By comparing the two hourly profiles (consumption and self-production of RES) it will be possible to determine, as a consequence, the quantity of electrical energy to be self-produced through traditional sources (i.e. microturbines) and, in case, the quantity of electrical energy to be purchased from/sold to the grid.

This model, which will be described in detail in subsection 2.1, acts under stochastic conditions through a DES simulator of the manufacturing plant. Its objective is to allow Energy Managers to optimize the use of available energy sources by knowing one day in advance of the lack or surplus of the hourly requirement compared to the quantity of producible energy, from both economic and environmental standpoints, attempting as much as possible to make use of renewable sources.

The second model, ERIM-RT, in completion of the first, acts on the current day, taking into account through the use of an online real-time DES simulator of what is happening in real time with the manufacturing plant (with projections repeated for each remaining hour of the day) and the actual instantaneous production of RES energy, due to the actual weather conditions. The use of a special predictive algorithm [21] provides, every 30 minutes, starting from the current weather situation, an update of the available RES energy production prediction for subsequent times of the day.

ERIM-RT, correcting the projections made through ERIM-P, helps to establish if and when to activate self-production from traditional sources and/or to access the electricity market in the subsequent hours of the day.

## 2.1 ERIM-P Model

The Energy Resources Intelligent Management-Predictor (ERIM-P) model was conceived with the objective of supporting energy managers in the manufacturing industries in planning the use of the various available RES and traditional sources, with the goal of reducing energy costs and minimizing environmental impact.

To identify the hourly energy production expected for the next day, special weather prediction sites must be used, which provide conditions for usability of such sources for each hour of the next day. The ERIM-P model translates the hourly producibility of the various RES sources into probability distribution functions and combines them using the Monte Carlo simulation.

The model's output provides the hourly availability of RES energy to supply the manufacturing plant. To obtain this result, the authors created a sub-model within ERIM-P called Internal Energetic Source Predictor (IESP), whose task is, as noted previously, to obtain an hourly profile of availability of RES electrical energy.

A second sub-model in ERIM-P consists of a DES simulator that reproduces the manufacturing plant. This simulator is kept online with the plant, and its purpose, at the end of each work day (starting from the current status of the plant and from the production plan for the next day), is to provide a consumption profile for each hour/half hour of the next day.

The two energy profiles supplied by the IESP model and the DES model feed the ERIM-P model, which develops the hourly energy plan for the next day (Figure 1).

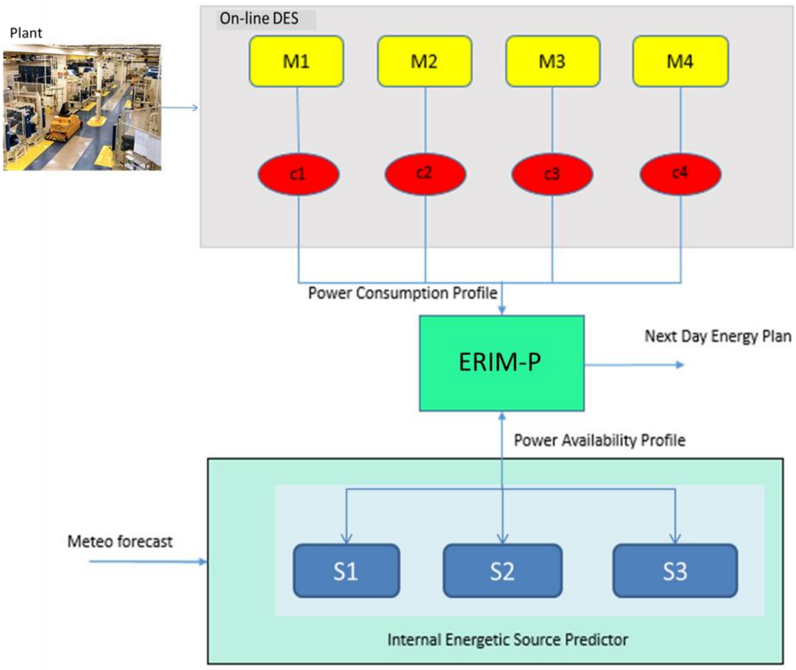


Figure 1 ERIM-P framework

In particular ERIM-P outputs, for every half-hour of the next day, the following data:

- X consumption of energy (KWh) required by the plant
- Y electrical energy self-produced by RES
- Y’ energy self-produced with other sources
- Y’ max maximum availability of self-production
- Y” energy that needs to be purchased on the electrical market

As already emphasized, knowing one day in advance the presumed behavior of the system as a whole will allow the Energy Manager to optimize, as much as possible, decisions regarding self-production, purchase, and/or sale of energy from/to the market.

### 2.1.1 Limits of ERIM-P

The use of a stochastic predictive approach using online DES and Monte Carlo simulators provides clear benefits in the capacity to describe the behavior of complex systems, leading to results that are absolutely consistent with the actuality of the system under examination. However, unpredictable events and/or extemporaneous decisions made by production management can create significant deviations between the consumption predicted by the simulator the day before and the reality of the following day.

In addition, the IESP model is based on hourly weather predictions which, though released by sources that are reliable and specialized, is also subject to randomness. Neither of the above considerations regarding the predictive capacity of the DES and Monte Carlo simulations compromise the validity of these methodologies, but, under certain conditions, they become a limit to the benefit of the proposed model. This is because the single or combined action of the two influences (variation in production and/or weather) can generate differences that also affect the economic results of energy management.

For this reason, the authors decided to supplement this model, which we can call “day-ahead”, with a model called ERIM-RT, or the “current day” model. Subsection 2.2 describes the additional model in detail, to be used as a supplement to the previous one.

## 2.2 ERIM-RT

This model is placed in conjunction to ERIM-P with the objective of overcoming the limitations described in the previous subsection 2.1.1. The core elements of ERIM-RT are: a DES simulator functioning online real-time with the plant and a predictive update algorithm for RES production, which is also an online real-time agent with weather conditions (Figure 2).

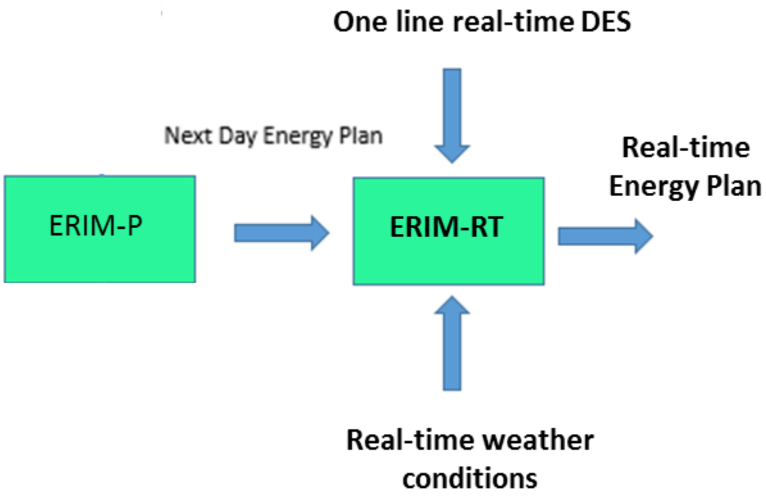


Figure 2 Input/Output schematization of ERIM-RT

Starting from the zero moment of the morning shift, the real-time simulator, every 30 minutes, receives the data for the current status of the plant (machine occupation and operators, breakdowns, production plans, changes thereof, etc.) and projects them along the entire arc of the production day. In this way, the hourly demand profiles, individual and total, calculated by ERIM-P the day before, are updated every 30 minutes based on actual operations and until the end of the working day, and thus the actual hourly quantity of energy that must be made available to the manufacturing plant for that day.

The predictive update algorithm for RES energy production recalculates, again every 30 minutes, based on the actual weather conditions at the site where the plant is located, the quantity of RES energy that it will be capable of producing from that moment until the end of the day. The additive algorithm is formulated as follows:

$$F_{k+i|k} = min\{F_{k+i|k-1} + M_k - F_{k|k-1}, P_p\}$$

where:

- $F_{k+i/k}$ is the prediction of power production made at the moment k of the day for all the remaining hours of the current day;
- $M_k$ is the quantity of power actually produced by RES at moment k;
- $F_{k/k-1}$ is the prediction of power production made at moment k-1 for the day for the moment K and, obviously, it cannot in any case exceed the peak power of the RES plant;
- $F_{k+i/k-1}$ is the prediction of the quantity of power produced at the moment k-1 for the day for the hours from K to the end of the day;
- Pp is the peak power of the RES plant.

The algorithm pseudocode can be defined as follows:

for k=0, 30, 60, 90, 120…..1440

If $A_k = F_{k+i|k-1}$

$$F_{k+i|k} = F_{k+i|k-1}$$

else

$$F_{k+i|k} = min\{F_{k+i|k-1} + M_k - F_{k|k-1}, P_p\}$$

where $A_k$ are the actual weather conditions

Following this logic, ERIM-RT is able to notably improve the performance of ERIM-P, although this model is in itself capable of providing significant improvements to the Energy Manager's decision-making process.

The benefit derives from the fact that, even if the predictions of ERIM-P for power demand for the next day are completely erroneous due to changing operating and/or weather conditions, ERIM-RT will be able to remediate inaccurate predictions. Obviously, the more energy-intensive the manufacturing processes and/or the higher their stochasticity, the more using ERIM-RT will yield significant economic results in terms of lower costs for energy used.

## 3. Application of the methodology to a real case

The plant taken into consideration for testing the proposed approach is a medium-sized manufacturing tannery, located in southern Italy in the tannery district of Solofra. Its annual production is on the order of 9,000 tons of hides treated, and the peak power used is on the order of 500 kW (in sizes of 55/65 kW for the major machines). The duration of individual processing cycles ranges from a few minutes per piece to approximately 20 hours for calcination and unhairing. The annual consumption of electric power is approximately 3 million kWh, while thermal energy consumption is approximately 2,500,000 kWh. The sum of the two amounts of consumption exceeds 5 Gwh/year, and therefore this particular tannery can be considered for all intents and purposes an "Energy Intensive" industrial process.

The tannery's capacity for self-production of electric power is provided by:

- a photovoltaic panel installation for a total of 700 kWp. The average DNI of the site is 1,750 kWh/M2
- 2 co-generative microturbines, supplied by natural gas, with a nominal electric power of 200 kW (with 33% efficiency) and thermal (water at 60-70°C) equal to 285 kW, for a total of efficiency of >80%.

To manage the self-production of electric power, tannery management decided to adopt eco-sustainability as a general rule. As a consequence, the objective is to produce, as much as possible, only the amount of energy strictly required for operation of the tannery, or to keep the difference between electric power consumed and electric power produced (ΔkWh) as close to zero as possible.

From this perspective, given that photovoltaic production is connected to exogenous factors, the way to minimize $CO_2$ emissions is to optimize management of the functioning of the 2 turbines.

For this tannery, the problem of the cost of eco-sustainability of kWh produced, once the cost of investment in energy production plants are amortized, can be framed as follows:

- for the photovoltaic installation, maintenance costs (cleaning of panels and possible replacement of inverters at a rate of one/two in 20 years) are to be taken into consideration
- for the microturbines, costs for gas and maintenance which are, overall, lower than costs for purchasing from the electric market, are to be taken into consideration.

Considering that in Italy, excess power to the electrical grid is sold at a price per kWh that is markedly lower than the price of purchasing from the same market, the tannery needs to use the co-generating microturbines to produce only what the tannery can use.

## 3.1 Modeling the tannery process through DES

The plant receives raw and salted hides and produces batches of wet blue leather, that is, hides that have completed the entire tanning process (Figure 3).

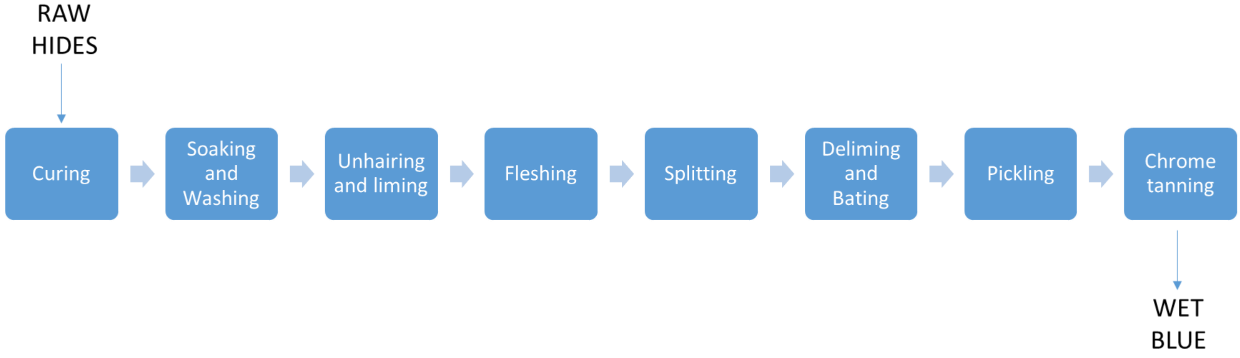


Figure 3: schematization of tanning process

Production takes place in three 8-hour shifts/day, six days a week. Using the Simul 8 software, a DES simulation model was developed for the entire hide processing cycle; thus it was possible to obtain output of the daily energy demand for the various machines operated. Stochasticity is included in the model through suitable probability density functions deduced from data gathered in the field, such as: duration of individual processing, breakdowns, ordinary maintenance, availability of employees, etc.

Since the DES simulation model is an essential component of both ERIM-P and ERIM-RT, its capacity to accurately reproduce the operating of the actual system is an indispensable element for obtaining real benefits from the proposed methodology. For this reason, in addition to statistical validation tests on the magnitude of the experimental error [22-24], the authors wanted to add a further verification test based on the congruency between the quantity of energy actually consumed by the tannery in a standard year and the quantity obtained from the simulator. The difference was on the order of 3%; that is, approximately 2,925,000 kWh simulated compared to 3,000,000 kWh consumed by the actual plant. We can therefore conclude that the DES model is fully capable of providing reliable data on the quantity of energy consumed by the tannery every 30-60 minutes, and it is therefore usable as a predictive tool, both for the demand for the next day (ERIM-P model) and the demand for the current day (ERIM-RT model).

### 3.2 Implementation of ERIM-P and ERIM-RT in the case study

The use of ERIM-P, compared to traditional management of the energy consumed by the tannery, can lead to significant benefits, both economically and environmentally (reduction of $CO_2$ emissions). In fact, the model allows, the day before, an initial optimization of the energy to be self-produced and/or purchased, acting on a behavior prediction that is very consistent with the reality of the tannery with regard to what the managers can predict. On the other hand, ERIM-RT acts on the current day, based on the predictions of ERIM-P, corrected online real-time, based on the instantaneous operations of the tannery. This provides further significant improvements to the Energy Manager's decision-making ability.
The advantages created by the use of ERIM-RT versus ERIM-P alone are illustrated in subsection 3.3 below, through an analysis of some typical days.

To facilitate comparison between the performance of the two models in economic and environmental terms, an appropriate KPI (Key Performance Indicator) called ΔkWh was introduced to measure the prediction error. This represents the difference between the kWh actually consumed by the plant and the energy requirement predicted by the model.

There are three possible cases:

1. ΔkWh = 0, that is, the model predicts, with no margin of error, both plant demand and RES production, such that the energy produced is the only energy consumed. Represents the ideal condition of maximum eco-sustainability;
2. ΔkWh < 0, the model overestimates energy production compared to actual demand. The excess energy produced can be sold on the electricity market;
3. ΔkWh > 0, the model underestimates the energy demand. Requires the production of a greater quantity of energy than the amount predicted. This can occur through the use of

the two 200 kWh microturbines present at the tannery and, if more energy is needed, through purchasing on the electricity market.

In both cases where ΔkWh is other than 0, the tannery could have an excess of $CO_2$ emissions, certainly in the third case (ΔkWh > 0), and possibly in the second case (ΔkWh < 0).

To estimate the benefit in terms of both economic and environmental impact, the following parameters were taken into consideration:

| | Production Cost (€/kWh) | Revenue (€/kWh) | $CO_2$ emissions (kg/kWh) |
|---|---|---|---|
| Microturbine | 0.11 | - | 0.45 |
| Photovoltaic | - | - | - |
| Grid | 0.25 | 0.08 | 0.45 |

### 3.3. Scenario analysis

To determine the economic benefits obtainable through use of the proposed methodology, 3 possible scenarios were taken into consideration:

- Scenario 1: the energy demand for the tannery estimated the day before is in line with actual consumption, while the hourly production from photovoltaic sources estimated the previous day is not in line with the actual availability for the day.
- Scenario 2: the energy demand for the tannery estimated the day before is not in line with actual consumption, while the hourly production from photovoltaic sources estimated the day before is in line with the actual availability for the day.
- Scenario 3: both the energy demand for the tannery and the production from photovoltaic source estimated the day before are in line with actual consumption/production

The three scenarios were compared with regard to the results obtained through the use of the ERIM-P predictive model alone versus those obtained through the addition of the ERIM-RT model.

#### 3.3.1 Scenario 1

In Figure 4, the energy demand predicted by ERIM-P DES is compared with the actual demand for the day. The analysis in Figure 4 shows that in the absence of particular random elements disrupting production, the DES simulator succeeds in faithfully reproducing, one day in advance, the operations of the tannery and the consequent energy demand over the various hours of the day.

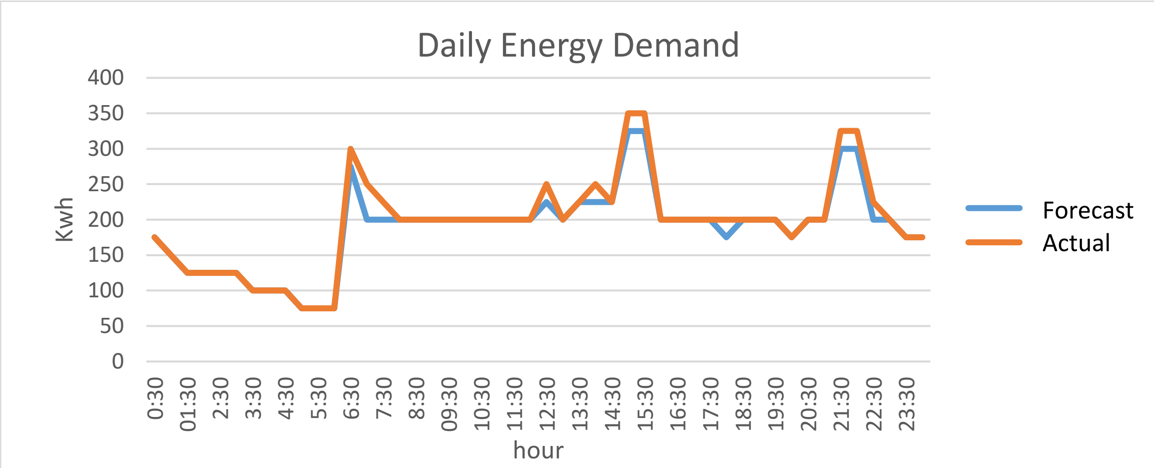


Figure 4: Daily energy demand for Scenario 1

Figure 5 shows the deviation between the production of photovoltaic energy estimated by the IESP sub-model of the ERIM-P and the energy actually produced the next day.

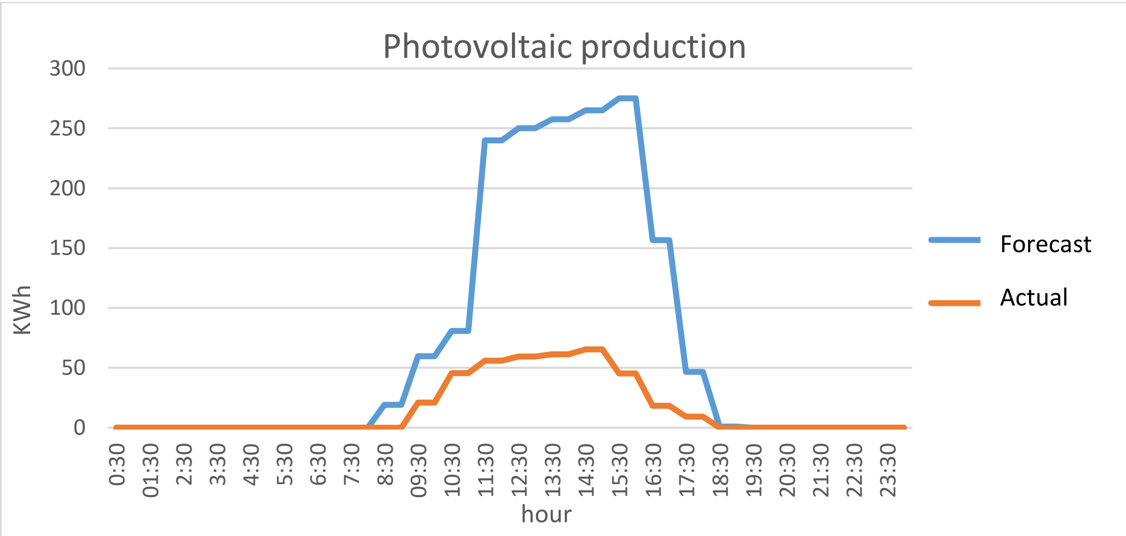


Figure 5 Photovoltaic production for Scenario 1

In Figures 6 and 7, we can detect the differing behaviors of ERIM-P and ERIM-RT in the situation described in this scenario. The application of ERIM-P (Figure 6) generates an underproduction, in particular during the central hours of the day, caused by incorrect planning for operation of the microturbines. To cover this instantaneous demand, it will be necessary to utilize the electrical power market or the unplanned operation of the turbines. On the other hand, the ERIM-RT model (Figure 7), through the predictive update algorithm, best uses the turbines, whose cost of production of kWh hours is lower than purchasing from the grid.

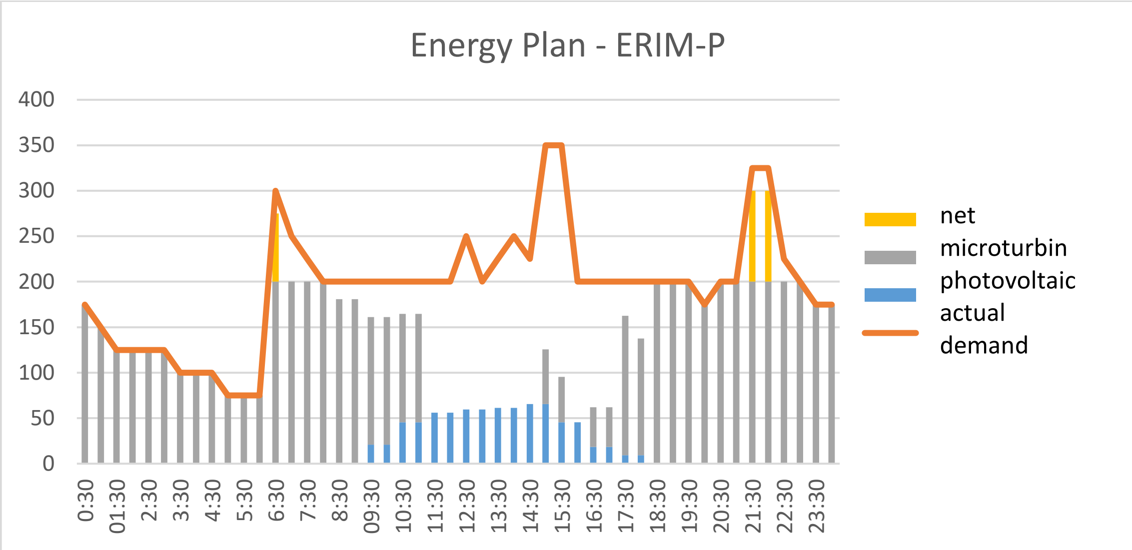


Figure 6 ERIM-P output for Scenario 1

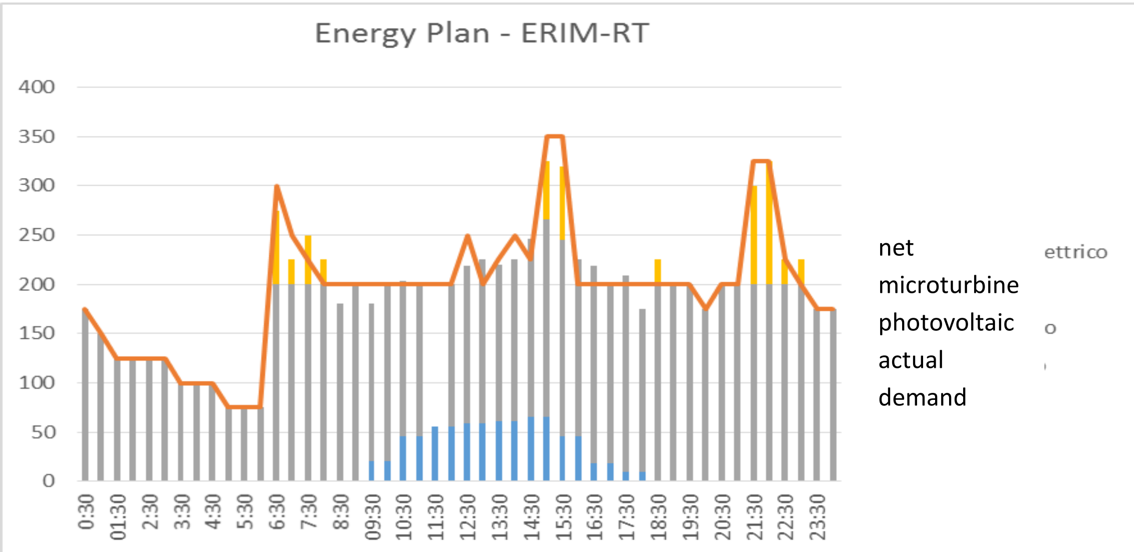


Figure 7 ERIM-RT output for Scenario 1

By comparing the results obtained with the two models, we can calculate the prediction errors committed by both and compare them:

- ERIM-P generates a negative ΔkWh equal to 2,328 kWh during daylight hours and 2,503 kWh throughout the entire day (24h)
- ERIM-RT generates a negative ΔkWh of 426 kWh during daylight hours and 501 kWh throughout the entire day (24h)

Considering the costs previously indicated for the energy produced by the turbines and for energy purchased from the market, a savings of approximately €300 is obtained by using ERIM-RT. If we were to consider instead that the weather prediction made the day before underestimates the production of photovoltaic energy, with ERIM-RT we would obtain a lower cost overall of approximately €30, but most importantly lower $CO_2$ emissions, equal to more than 815 kg.

### 3.3.2 Scenario 2

A day is taken into consideration where the energy demand for the current day is greater than what was predicted the day before due to the extemporaneous insertion of further requests for the product. The hourly weather conditions for the current day are, on the other hand, in line with the predictions of the prior day.

The graphics in Figures 8 and 9 show the difference, ex post, of the behavior of the two models, which is accentuated all the more by the unpredictable exogenous interference, which becomes significant for the current day. The comparison also shows greater coverage with self-production from turbines, in non-daylight hours, by the supplemental model ERIM-RT, while the single model ERIM-P would force purchases on the electrical power market to handle the instantaneous, unpredicted demand.

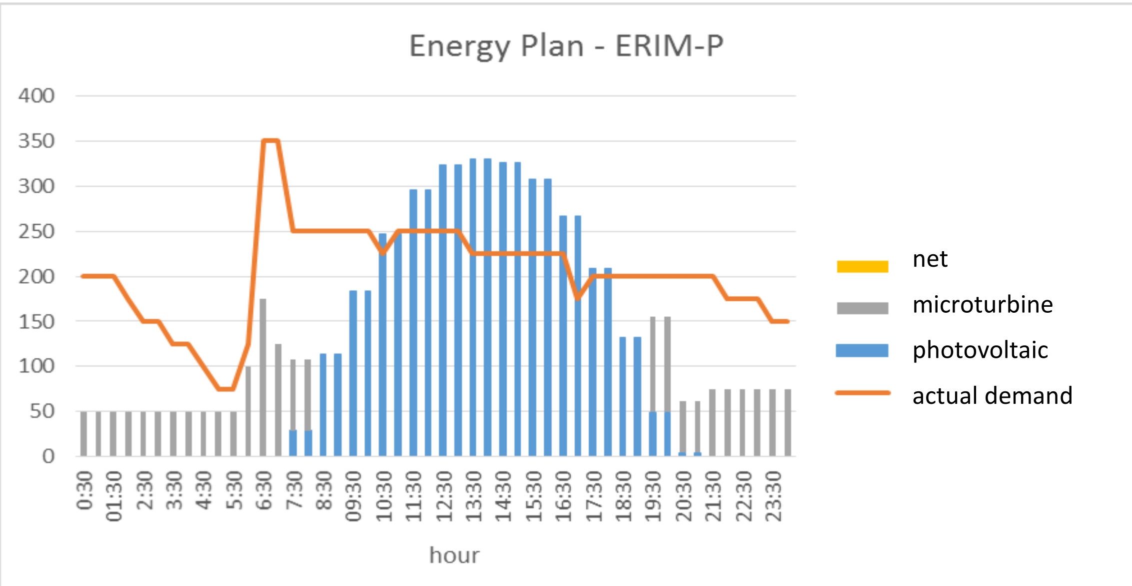


Figure 8 ERIM-P output for Scenario 2

The predictive error in production, attributable to the change of operating conditions the next day, generates an increase in the tannery's energy consumption of more than 3,200 kWh.
The ERIM-RT double model's responsiveness to exogenous events decreases this value by more than 2,500 kWh, and so to only 700 kWh.
As a consequence, the costs of the predictive error are practically doubled from €0.12/kWh to €0.25/kWH.

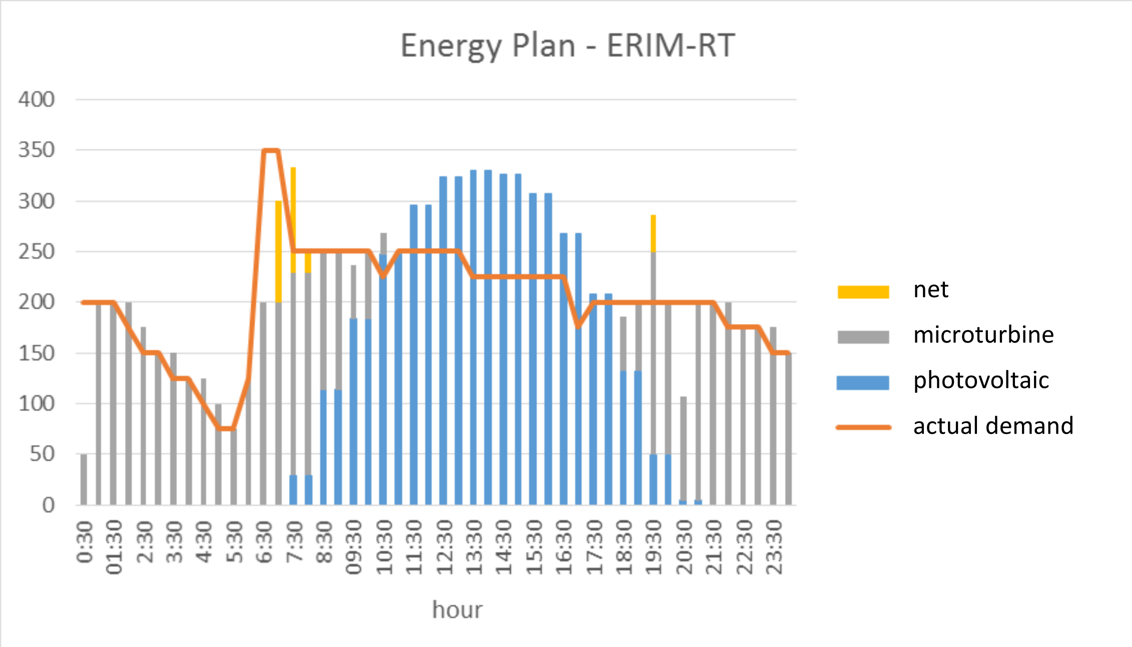


Figure 9 ERIM-RT output for Scenario 2

Economically, the advantage created by ERIM-GM, derived from the sale of photovoltaic power, is quantifiable at approximately €360. As in Scenario 1, we now analyze the opposite case, where the energy demand is markedly lower compared to the predictions of the previous day. In this case the ERIM-GM helped reduce the cost of ΔkWh by 10% and halved (-52%) $CO_2$ emissions.

### 3.3.3 Scenario 3

A day was taken into consideration where there were significant deviations both in terms of consumption and production of RES electric power. Under these conditions, the ERIM-RT model increases its performance possibilities compared to the ERIM-P model alone.
Depending on whether the deviations between the actual situation and the prediction (both in terms of demand and RES production) are positive or negative, 4 sub-scenarios can be identified:

- DLPH(Demand Lower Production Higher): predicted demand lower than actual demand and predicted RES production higher than actual RES production
- DLPL(Demand Lower Production Lower): predicted demand lower than actual demand and predicetd RES production lower than actual RES production
- DHPH (Demand Higher Production Lower): predicted demand higher than actual demand and predicted RES production higher than actual RES production
- DHPL(Demand Higher Production Lower): predicted demand higher than actual demand and predicted RES production lower than actual RES production

#### 3.3.3.1 Scenario DLPH

The prediction of energy demand, developed by ERIM-P DES, is lower than the next day ex post, while the photovoltaic production predictions mad e by IESP are greater than those actually realized. In other words, the energy consumption demanded by the tannery by DES for the following day is greater than predicted, while IESP overestimated photovoltaic production due to an unexpected disturbance.

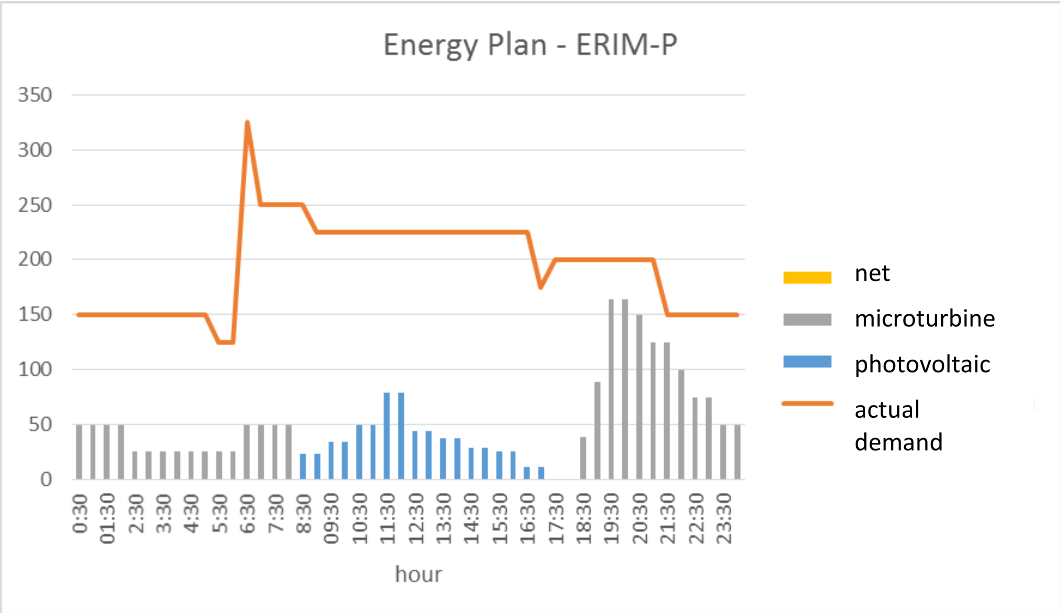


Figure 10 ERIM-P output for Scenario DLPH

Under these conditions, ERIM-P generates a ΔkWh of approximately 7,000 kWh, while ERIM-RT generates an error of only 900 kWh. ERIM-P, predicting less energy consumption than the actual, undersizes the use of the turbines, with the related penalties in terms of costs (having to go onto the electrical market for the missing quantity) (Figure 10 and Figure 11).

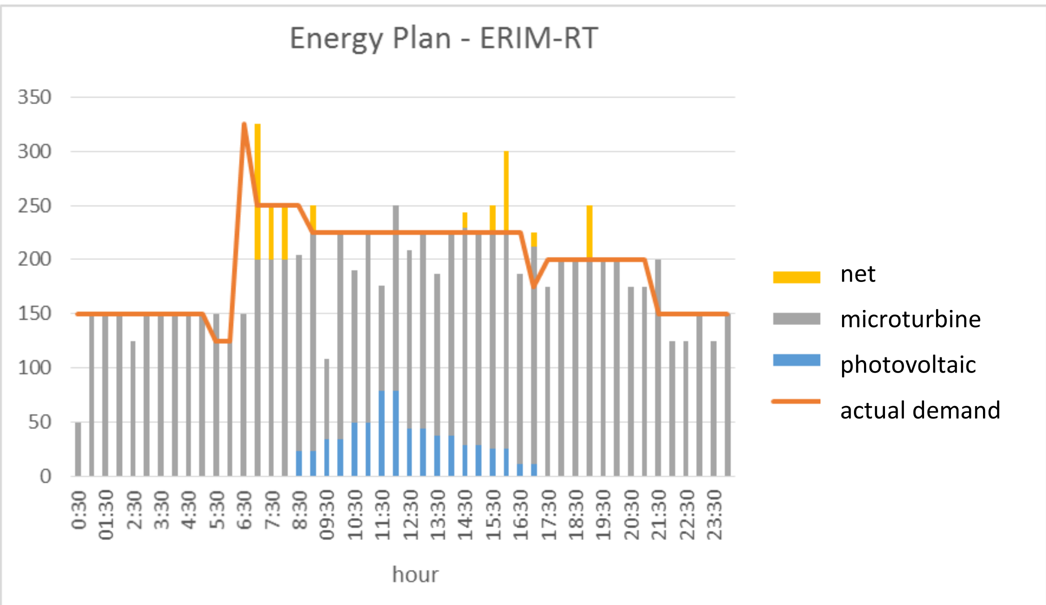


Figure 11 ERIM-RT output for Scenario DLPH

However, ERIM-RT recognizes, thanks to online real time update mechanisms, the changed conditions of energy demand and production, allowing a savings of approximately €900, equal to 45% of the cost developed by ERIM-P.

3.3.3.2 Scenario DLPL

The prediction of energy demand by the DES of ERIM-P for the next day is less than the total, as in the prediction for photovoltaic production made by IESP. In this scenario, the ERIM-P simulator predicts an hourly energy consumption profile that is lower than the actual profiles for the next day, and IESP provides a profile for energy actually available that is lower than the actual one for the day after. The related predictive error by ERIM-P is -4,270 kWh, while the one made by ERIM-GM is reduced by approximately one-fifth, or -925 kWh (Figures 12 and 13).

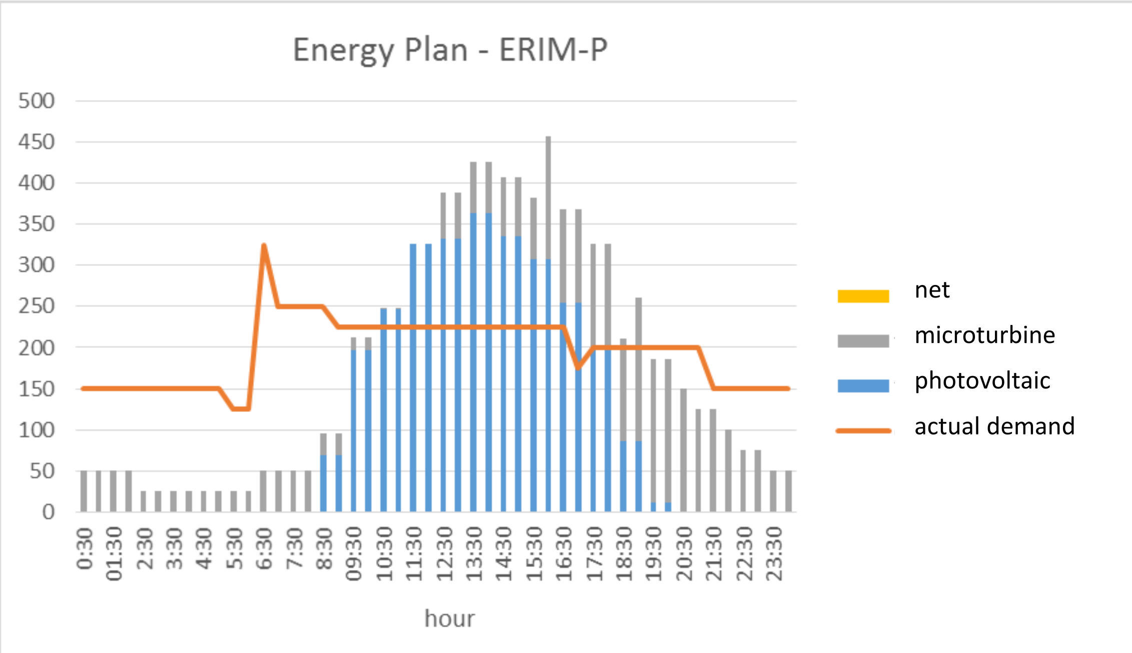


Figure 12 ERIM-P output for Scenario DLPL

This occurs because the reduced need for energy predicted by ERIM-P causes less planning for the use of the turbine, with the consequent need to then instantaneously buy from the electrical energy market, with the consequent increase in costs. Under these conditions, ERIM-RT brings savings in terms of energy costs of about 35% (equal to €355/day) compared to ERIM-P. The benefits to the ecosystem under these conditions generated by the use of ERIM-RT consists in $CO_2$ emissions reduced by approximately 390 Kg.

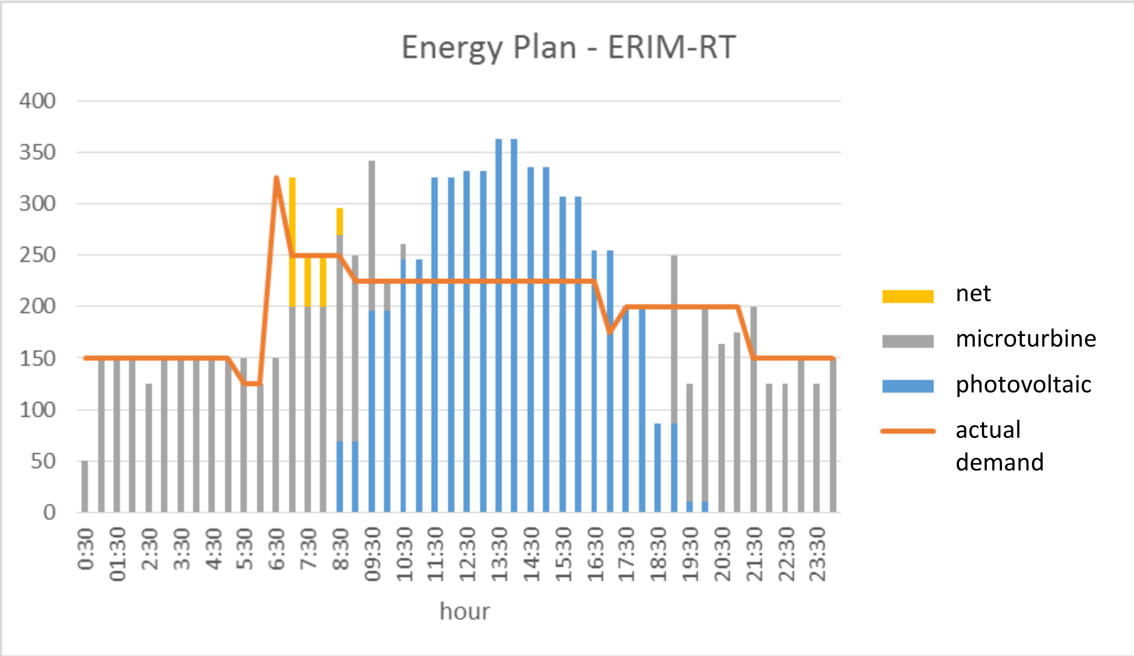


Figure 13 ERIM-RT output for Scenario DLPL

### 3.3.3.3 Scenario DHPH

The prediction of electrical consumption by ERIM-P DES higher than what is realized the next day. Based on weather predictions, IESP predicts photovoltaic production greater than what is actually realized on the current day. In this case as well, the integrated ERIM-GM model is clearly more reliable, since it reduces to one-quarter the predictive error for electrical energy (approximately 1,000 kW hours compared to 4,000 kWh predicted by ERIM-P), with an economic benefit of approximately €230 over 24 hours. With regard to $CO_2$ emissions, ERIM-P would involve the production of 2,703 Kg in 24 hours, compared to 1,665 kg for ERIM-RT.

### 3.3.3.4 Scenario DHPL

ERIM-P DES predicts for the following day an energy profile greater than what is actually recorded, while IESP, based on weather predictions, underestimates RES production.

In this case, the utility of the ERIM-GM model is even greater. This is because with a ΔkWh of 6,600 kWh for ERIM-P, the ΔkWh of ERIM-RT is only 700 kWh. In terms of $CO_2$, with ERIM-P emissions would have been equal to 3,800 kg, while ERIM-RT allows a reduction of 1,000 kg.

## 4 Results and Discussions

With reference to the test cases conducted on the tannery, the results illustrated show that the ERIM-RT model allows the obtaining of significant improvements in real time estimates, both of daily energy demand schedule and actual photovoltaic production obtainable (with consequently more efficient planning of self-production with turbines and/or purchasing from suppliers). In demonstration of this, in the four combined high-variability sub-scenarios below (DLPL,DLPH,DHPL,DHPH) examined for Scenario 3, we found a clear improvement in energy performance for the tannery in terms of reduction of error, $CO_2$ emissions, and energy costs.

ERIM-RT is more effective the larger the deviations are between the prediction made on the day before and the actual profiles (consumption/self-production/purchase) for the current day. This is because the tannery, like any other manufacturing system, is characterized not only by stochasticity, reasonably predictable by pdf, but also by randomness. For this reason, the more the behavior of the tannery is affected by randomness (in terms of demand versus energy production), the more the use of the ERIM-RT model becomes essential. To better understand these statements, one need only take into consideration the two sub-scenarios DLPH and DHPL. In fact, with these the ERIM-RT model leads to improvements in predictive performance respectively 7.3 and 7 times greater than with the ERIM-P predictive model alone.

## 5 Conclusions

The correct management of energy, particularly electrical energy, is an important contribution to sustainability. The term "sustainable", when applied to the use of energy, is evoked, on the one hand, in the search for less consumption per unit produced, and on the other hand, in the growing use of self-production through Renewable Energy Sources (RES). For this reason, the meeting on the state of the planet held in Paris in December 2015 established that investments in RES must grow significantly and that, by 2020, the longest-industrialized countries will supply €100 billion/year from public and private investments to convert traditional electric power plants into eco-sustainable plants. This figure may be increased every five years, if necessary. This agreement was ratified by the UN on April 22, 2016 in New York.

In developing the intelligent energy management model presented in this paper, the authors consciously kept these guidelines in mind.

The paper presents a supporting tool for energy managers in manufacturing sector. It uses a discrete event simulation DES (online and online real time), Monte Carlo simulation and a special predictive algorithm. The major target for this paper is the optimization of the energy supplying mix (self-production from renewable and not renewable sources and/ or purchase on the electricity market) to minimize Co2 emissions and company total cost.

The major contribution of this paper is its methodology. It uses the ERIM-P data prediction (hourly energy needed for the manufacture plant, hourly quantity of self-production of RES energy and energy used from traditional resources either by purchasing or selling to the grid) and combines it with a ERIM-RT real time data of manufacture plant and weather conditions using special predictive algorithm to correct the projection of the data required.

The real application presented, related to an Italian tannery, demonstrates that the proposed approach, thanks to the integrated and optimized management of RES and non-RES sources of production, can provide consistent benefits for energy savings and consequently environmental emissions.

## 6 Future developments

The energy model presented in the paper can be extended to three further aspects, again with the aim of improving economic and environmental performance. The first is the possible inclusion of thermal energy demands in the ERIM-RT model.

The second is related to the transfer of excess electrical energy produced. Currently the tannery, like many other small- and medium-sized Italian companies, sells these excesses to the electrical grid. These are remunerated at a lower price than the cost of production with microturbines. This gives rise to the idea of using an appropriate variant of the proposed methodology to allow small and medium companies to, from time to time, sell energy on the market that provides them with the most favorable conditions, knowing with a good deal of accuracy the day before of the excess energy to be produced in the various hours of the day.

The third aspect that can be considered could be the presence of an energy storage that could improve the use of the energy produced by RES sources, reducing sales and purchases from the grid.

## References

[1] May G, Stahl B, Taisch M, Kiritsis D. Energy management in manufacturing: From literature review to a conceptual framework. Journal of Cleaner Production, in press,

[2] Yong JY, Klemeš JJ, Varbanov PS, Huisingh D. Cleaner energy for cleaner production: modelling, simulation, optimisation and waste management, Journal of Cleaner Production, Volume 111, Part A, 16 January 2016, Pages 1–16.

[3] Azcárate C, Mallor F, Mateo P. Tactical and operational management of wind energy systems with storage using a probabilistic forecast of the energy resource. Renewable Energy Volume 102, Part B, March 2017, Pages 445–456.

[4] Bornschlegl M.,Bregulla M, Frankeb J. Methods-Energy Measurement – An approach for sustainable energy planning of manufacturing technologies. Journal of Cleaner Production Volume 135, 1 November 2016, Pages 644–656

[5] Piltan M, Shiri H, Ghaderi SF. Energy demand forecasting in Iranian metal industry using linear and nonlinear models based on evolutionary algorithms. Energy Conversion and Management, Volume 58, June 2012, Pages 1-9.

[6] Paolucci M, Anghinolfi D, Tonelli F. Facing energy-aware scheduling: a multi-objective extension of a scheduling support system for improving energy efficiency in a moulding industry. Soft Computing, 2015, pp 1–12.

[7]Filik ÜB, Gerek ÖN, Kurban M. A novel modeling approach for hourly forecasting of long-term electric energy demand. Energy Conversion and Management, Volume 52, Issue 1, January 2011, Pages 199-211

[8] Zhu Q, Lujia F, Mayyas A, Omar M.A., Al-Hammadi Y, Al Saleh S. Production energy optimization using low dynamic programming, a decision support tool for sustainable manufacturing. Journal of Cleaner Production, Volume 105, 15 October 2015, Pages 178–183

[9] Masa-Bote D, Castillo-Cagigal M, Matallanas E, Caamaño-Martín E, Gutiérrez A, Monasterio-Huelín F, et al. Improving photovoltaics grid integration through short time forecasting and self-consumption. Applied Energy, Volume 125, 15 July 2014, Pages 103-113

[10] Li N, Wang K, Cheng J. A research on a following day load simulation method based on weather forecast parameters, Energy Conversion and Management, Volume 103, October 2015, Pages 691-704

[11] Amrouche B, Le Pivert X.Artificial neural network based daily local forecasting for global solar radiation. Applied Energy, Volume 130, 1 October 2014, Pages 333-341

[12] Benmouiza K, Cheknane A. Forecasting hourly global solar radiation using hybrid k-means and nonlinear autoregressive neural network models. Energy Conversion and Management, Volume 75, November 2013, Pages 561-569

[13] Coelho VN, Coelho IM, Coelho BN, Reis AJR, Enayatifar R, Souza MJF et al. A self-adaptive evolutionary fuzzy model for load forecasting problems on smart grid environment. Applied Energy, Volume 169, 1 May 2016, Pages 567-584

[14]Pascual J, Barricarte J, Sanchis P, Marroyo L. Energy management strategy for a renewable-based residential microgrid with generation and demand forecasting. Applied Energy, Volume 158, 15 November 2015, Pages 12-25

[15]Barillari L, Bendato I, Bonfiglio A, Bracco S, Brignone M, Delfino F et al. Day Ahead Microgrid Optimization: A Comparison Among Different Models. Proceeding of OPT-i International Conference on Engineering and Applied Sciences Optimization, Kos Island, Greece, 4-6 June 2014.

[16]Ghani U, Monfared R, Harrison R. Real Time Energy Consumption Analysis for Manufacturing Systems Using Integrative Virtual and Discrete Event Simulation, International Journal of Energy Engineering (IJEE), 2012, 2 (3), pp. 69 - 73.

[17]Kouki M, Castagna P, Cardin O, Cornardeau C. An energy-related discrete event simulation approach 11° Congres International De Genie Industriel – Cigi2015, Québec, Canada, 26-28 Octobre 2015

[18] Beier J, Thiede S, Herrmann C. Energy flexibility of manufacturing systems for variable renewable energy supply integration: Real-time control method and simulation. Journal of Cleaner Production, Volume 141, 10 January 2017, Pages 648–661.

[19]Bendato I, Cassettari L, Mosca M, Mosca R. New Markets Forecast and Dynamic Production Redesign Through Stochastic Simulation, International Journal of Simulation Modelling, 14(3), 2015.

[20] Cassettari L, Mosca R, Revetria R, Rolando F. Sizing of a 3,000,000t bulk cargo port through discrete and stochastic simulation integrated with response surface methodology techniques. Recent Advances in Signal Processing, Computational Geometry and Systems Theory - ISCGAV'11, ISTASC'11.

[21] Bendato I, Bonfiglio A, Brignone M, Delfino F, Pampararo F, Procopio R. A real-time Energy Management System for the integration of economical aspects and system operator requirements: Definition and validation. Renewable Energy, Volume 102, Part B, March 2017, Pages 406–416

[22] Cassettari L, Mosca R, Revetria R. Experimental error measurement in monte carlo simulation. In: Abu-Taieh EMO, El Sheikh AAR, editors. Handbook of Research on Discrete Event Simulation Environments: Technologies and Applications. IGI Global, 2009, pp 92-142

[23] Bendato I, Cassettari L, Giribone PG, Mosca R. Monte Carlo method for pricing complex financial derivatives: An innovative approach to the control of convergence. Applied Mathematical Sciences, 2015.

[24] Mosca R, Bruzzone AG, Cassettari L, Mosca M.  Risk analysis for industrial plants projects: An innovative approach based on simulation techniques with experimental error control. 21st European Modeling and Simulation Symposium, EMSS 2009.