IMPACT OF THE FORECAST PRICE ON ECONOMIC RESULTS FOR METHANOL PRODUCTION FROM OLIVE WASTE

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Abbreviations	
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
DC	Deterministic Case
DT	Damped Trend
EU	European Union
IDD	Independent and Identically Distributed
IRR	Internal Rate of Return
LLT	Local Linear Trend
LLTC	Local Linear Trend with cycle
NPV	Net Present Value
PSA	Pressure Swing Adsorption
RW	Random Walk
SS	State Space
UC	Unobserved Components
VaR	Value at Risk
75op25P	75 wt.% of olive pomace and 25 wt.% of petcoke

Abstract

The development of circular economies due to the limitation of natural resources is becoming a common strategy of paramount importance among different countries. In Spain, given the strategic nature of its olive industry, trying to value one of its main residuals (olive pomace) alone or together with other residues through its chemical transformation in methanol is a promising research line. One of the key variables that would make the investment advisable or not is the future value of the methanol price. However, most of the literature do not consider its future price volatility on the economic evaluation of the chemical processes. This work bridges that gap by proposing three econometric models based on Unobserved Components to forecast the methanol price over the life cycle plant. Those probabilistic forecasts feed a Monte Carlo simulation that provides an exhaustive investment risk assessment in terms of Net Present Value, Internal Rate of Return and Value at Risk metrics. The results showed the relationship between forecasting models and the investment profitability with an average Internal Rate of Return ranging from 23% to 31%. Additionally, the previous analysis was completed by adding other variables subject to uncertainty (olive pomace feed, capital investment, feedstock price, labor costs and discount rate). In this case, assuming a potential underestimation error up to 100% of the capital cost the probability of obtaining a profitable investment was significantly reduced ranging the Value at Risk from 48% to 98%.

Keywords: co-gasification; methanol; olive pomace/petcoke; forecasting; Monte Carlo simulation; Value at Risk.

1. Introduction

Methanol is rated among the top chemical commodities produced worldwide, which can be used directly as a clean and cost-alternative fuel or can be mixed with other conventional fuels. Furthermore, methanol plays an important role in the global economy as the main raw material for many chemical industries like formaldehyde, methyl tertiary butyl ether, acetic acid and gasoline. From a thermodynamic point of view, using methanol in internal combustion engines could have different benefits such as an increase in both, power (due to the engine's compression rate increase) and energy efficiency [1]. In addition, their use reduces the pollutants release.

On an industrial scale, the methanol is principally produced from natural gas by reforming it with steam. However, other feedstocks can be used, being the coal widely used as a feedstock for methanol production in China [2]. The main problem associated with the methanol production from fossil resources are the emissions of large amounts of greenhouse gases, concretely about 0.6-1.5 tons of CO_2 per ton of methanol can be emitted into atmosphere [3].

Worldwide, there are currently around 90 industrial plants which have a production capacity of about 110 million ton [4], of which 10% come from Europe. Concretely, Spain produces approximately 6% of European production [5]. On the demand behalf, European methanol demand is becoming increasingly dependent on imports to feed its market [5] and Spain´s methanol demand is expected to grow significantly in the next years due to its widespread use in the chemical and process industries [6]. Spain's methanol demand is principally focused on the formaldehyde sector. Acetic acid and fuels are the other two main methanol end-use markets. For this reason and due to the Spanish dependence on imports from outside the EU of both methanol and natural gas, which causes a situation of vulnerability in case of supply shortages or price increases, the interest for academics and specialists alike has increased to research new sustainable alternatives. For that reason, numerous studies have focused on the green methanol production. In this sense, Simon et al. (2020) studied different renewable ways, in particular they focused on fuel cells to obtain green methanol [7]. Bazaluk et al. (2020) analysed the methanol production using biomass waste and wind power [8] and Samimi et al. (2019) evaluated the methanol production from indirect CO_2 conversion [9]. Nonetheless, among the non-fossil production alternatives, methanol obtained through biomass gasification is considered as an appropriate candidate to substitute conventional methanol from natural gas [10], favoring the circular economy of Spain, helping to reduce climate change and decreasing such a dependence.

The co-gasification of biomass and petcoke is a good alternative since synergies can be found in the co-gasification process [11], reducing the biomass inconvenience due to its uncertain supply. The selected biomass is olive pomace, since the olive industry is one of the most important for the Spanish economy, and in recent years it is presenting a significant price depression, thus revaluing their products may strength that sector and enhance Spanish circular economy. In the case of petcoke, it is an abundant by-product which is often used for energy production. However, its valorization through gasification is more environmentally friendly and versatile, since the gas product of gasification can be used in several applications. In this sense, it can be burnt directly, used either as fuel for gas turbine or to produce added value chemicals [12]. Therefore, the use of these Spanish wastes contributes to meet the three main objectives of sustainability: social cohesion, economic development and environmental protection.

Undertaking a green project with new technologies on an industrial scale requires a substantial investment. To minimize the risk of the investment, previous tecno-economic analyses are required to estimate the potential profits of such an investment. These economic studies are typically calculated using investment selection techniques such as net present value (NPV) and internal rate of return (IRR), among others. Note that NPV and IRR are different metrics of the discounted cash flow method. In this context, there are two methods to calculate these relevant investment criteria: deterministic and stochastic. The first is the most common in literature [2, 13-19] and it considers that all the variables deemed are constant and known during the life of the project. However, such a restrictive assumption can result in important estimation errors when the unknown variables are highly volatile, making the results of the economic viability not reliable. On the other hand, a stochastic perspective consists of replacing the constant variables with random variables that follows a certain statistical distribution. This approach evaluates the investment risk and can be carried out by means of Monte Carlo simulations [20]. In this sense, references [21-29] employed Monte Carlo simulations, where the variables considered as a source of uncertainty were introduced by assuming statistical probability distributions.

Nonetheless, if the key variables under study are not IID (independent and identically distributed), i.e., they present a trend, seasonal or cycle component, we must go one step further and using forecasting models to estimate the future probabilistic value of such key variables that will feed Monte Carlo simulations. In this regard, in a previous work, an economic assessment of methanol production from syngas obtained through biomass was carried out from both a determinist and stochastic perspective [30]. Following a deterministic approach, it was observed that the methanol price was the variable that most influenced in the economic viability as it was also acknowledged in [13]. For that reason, a preliminary stochastic study was carried out to investigate the uncertainty associated with the methanol price. In that case a Damped Trend forecasting model was used to forecast the methanol price.

In this work, our aim is twofold: i) to propose improved methanol price forecasting models than those used *by Puig-Gamero et al.* [26]. Essentially, methanol price time series presents components as a trend and a cycle that were not explored, and its inclusion might result in more accurate forecasts. Here, Unobserved Components forecasting models able to cope with the presence of trend/cycle patterns are developed in a State Space framework to provide methanol price probabilistic forecasts. To the best of authors' knowledge, this is the first time these models are used to forecast methanol price; ii) to extend the risk assessment done in [26] by including other sources of uncertainty such us raw material cost, raw materials feed, capital investment, labor cost, the discount rate, among others. Such uncertainty variables are incorporated in the Monte Carlo simulations by assuming them random variables that follows a certain statistical distribution.

Therefore, this article has been organised as follows: Section 2 explains the potential components of the methanol price time series and the proposed forecasting models. Section 3 describes the case study and the economic metrics. Section 4 is devoted to the uncertainty analysis. Finally, the main conclusions are drawn in Section 5.

2. Forecasting models of the methanol price

Forecasting is a vital task in energy applications, particularly, in a renewable energy context due to the lack of solutions for energy storage in power plants. See, for instance, some works related to wind energy [31] and solar energy [32-34]. Regarding price forecasting, literature is mainly focused on electricity time series [35, 36] and crude oil [37], whereas, price forecasting of other crucial energy variables as Natural gas is less common [38]. In fact, to the best of authors' knowledge, forecasting of the methanol price is totally overlooked on the scientific literature, even though the price of methanol has been identified as the most influential variable affecting the economic viability in some processes as [13]. We have only found some consultancy companies that provide those forecasts, which are not freely available. One of the main contributions of this work is to provide different methanol price forecasting models depending on the Unobserved Components (trend and/or cycle) identified in the data.

In this work, methanol past prices from 2000 to 2018 are utilized to compute forecasts. The original data is monthly sampled, and it has been aggregated to a yearly basis, since we need yearly forecasts. Figure 1 shows the methanol prices in a dashed line with blue circle markers. In that plot, we can appreciate the potential presence of a trend and cycle component. That cycle component could be originated due to business cycles [13].

2.1 Unobserved Components models

The forecasting technique employed must be one capable of accommodating those components seen in the data. An appropriate approach to that end is the family of Unobserved Components (UC) models that, in the case of annual data with a cycle, takes the general form shown in equation (1) [39-41].

$$y_t = T_t + C_t + I_t \tag{1}$$

where y_t, T_t, C_t and I_t stand for the data, trend, cyclical and irregular components, respectively.

The model is completed by selecting the particular dynamic behaviour of each of the components. There have been different alternatives to deal with this sort of decomposition, though the inclusion of the cycle is not common. From all of them, the structural approach set up in a State Space (SS) framework is the most widespread [40].

The trend deals with the long term dynamic behaviour of the time series. The first model considered in this work is a Damped Trend (DT) model shown in equation (2).

$$\begin{bmatrix} T_{t+1} \\ T^*_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & \alpha \end{bmatrix} \begin{bmatrix} T_t \\ T^*_t \end{bmatrix} + \begin{bmatrix} \eta_{1,t} \\ \eta^*_{1,t} \end{bmatrix} \tag{2}$$

where T^*_t is referred to as the trend `slope', α is the damping parameter ($0 < \alpha \leq 1$), and $\eta_{1,t}$ and $\eta^*_{1,t}$ are independent white noise sequences with variances σ^2_1 and σ^{2*}_1, respectively.

This model actually subsumes the following particular cases, often found in the literature: i) Random Walk (RW), with $\alpha = 0$, $\sigma_1^{2*} = 0$ and $T_1^* = 0$; ii) Random Walk with drift (= 0, $\sigma_1^{2*} = 0$ and $T_1^* \neq 0$); iii) Integrated Random Walk (IRW, $\alpha = 1$, $\sigma_1^2 = 0$); and iv) Local Linear Trend (LLT, $\alpha = 1$). All these trends are stochastic and have at least one unit root ensuring they are not stationary.

The cycle component is responsible of the oscillations of period longer than one year. The model is shown in equation (3), where C_t^* is an auxiliary measure necessary to define the stochastic behavior of the component C_t. In the same equation, the parameter ρ controls the persistency of the cycle ($0 < \rho \leq 1$), ω is the frequency associated to the cycle ($\omega = 2\pi/P$, where P is the period in number of observations per cycle), and $\eta_{2,t}$ and $\eta_{2,t}^*$ are independent white noise sequences with common variance σ_2^2.

$$\begin{bmatrix} C_{t+1} \\ C_{t+1}^* \end{bmatrix} = \rho \begin{bmatrix} \cos\,\omega & \sin\,\omega \\ -\sin\,\omega & \cos\,\omega \end{bmatrix} \begin{bmatrix} C_t \\ C_t^* \end{bmatrix} + \begin{bmatrix} \eta_{2,t} \\ \eta_{2,t}^* \end{bmatrix} \tag{3}$$

Finally, the irregular component is simply white noise with mean zero and constant variance σ^2.

The structural UC approach proceeds by block concatenating all the components models involved in a single linear Gaussian SS system, with equation (1) playing the role of the observation equation. The full SS system is shown in equation (4).

$$\begin{gathered} \begin{bmatrix} T_{t+1} \\ T_{t+1}^* \\ C_{t+1} \\ C_{t+1}^* \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & \alpha & 0 & 0 \\ 0 & 0 & \rho\cos\,\omega & \rho\sin\,\omega \\ 0 & 0 & -\rho\sin\,\omega & \rho\cos\,\omega \end{bmatrix} \begin{bmatrix} T_t \\ T_t^* \\ C_t \\ C_t^* \end{bmatrix} + \begin{bmatrix} \eta_{1,t} \\ \eta_{1,t}^* \\ \eta_{2,t} \\ \eta_{2,t}^* \end{bmatrix} \\ y_t = [1 \quad 0 \quad 1 \quad 0] \begin{bmatrix} T_t \\ T_t^* \\ C_t \\ C_t^* \end{bmatrix} + I_t \end{gathered} \tag{4}$$

Optimal values of the states and their covariance matrices may be estimated by well-known recursive algorithms, namely the Kalman Filter and Fixed Interval Smoothers. Application of such algorithms require knowledge of all the matrices involved, that depend on a number of unknown parameters, namely α, ρ, ω, σ_1^2, σ_1^{2*}, σ_2^2 and σ^2. Estimation is usually carried out by Maximum Likelihood by repeated runs of the recursive algorithms on different sets of parameters and aided by a searching algorithm, see details in [39-41].

2.2. Methanol price forecasts.

Figure 1 (a) shows forecasts for the next 15 years (2020-2034) computed by the DT model. Forecasts of Figure 1 (a) are shown via a fan chart [42], where the dashed line with blue circle markers shows the past data and the solid black line is the point (mean) forecast of the methanol price. That plot also gives a measure of the range of uncertainty through the shaded area around the central projection. That uncertainty was calculated by using the forecast errors from the previous years (2000-2018). It is also assumed that forecast errors follow a gaussian distribution. The fan chart of Figure 1 shows the alternative scenarios of the future methanol price that will be used as inputs for the Monte Carlo simulations with 10000 repetitions. Given that the simulations are normally sampled, there will be more scenarios around the mean (black line) than in the extremes. In other words, it is more likely to have more scenarios where the shaded area gets darker. Note that, as a consequence of the high uncertainty some extreme scenarios could consider negative methanol prices, which is unrealistic and, therefore, those cases have been truncated to zero.

Analyzing methanol prices between 2000 and 2018 one could identify the presence of a trend and, even a cycle. Therefore, Local Linear Trend (LLT) and Local Linear Trend with cycle (LLTC) are forecasting models capable of incorporating such components, respectively. Figure 1 (b) and (c) depict the forecasts produced by LLT and LLTC. Figure 1 (b) shows a positive trend, note that authors in [13] also considered a positive trend in their deterministic forecasts, see Figure 3 in reference [13]. Figure 1 (c) considers the trend component and the cycle, whose period of 6.78 years was also identified via Maximum Likelihood, [36]. All these models are implemented in a MATLAB toolbox called SSPACE [43].

c)

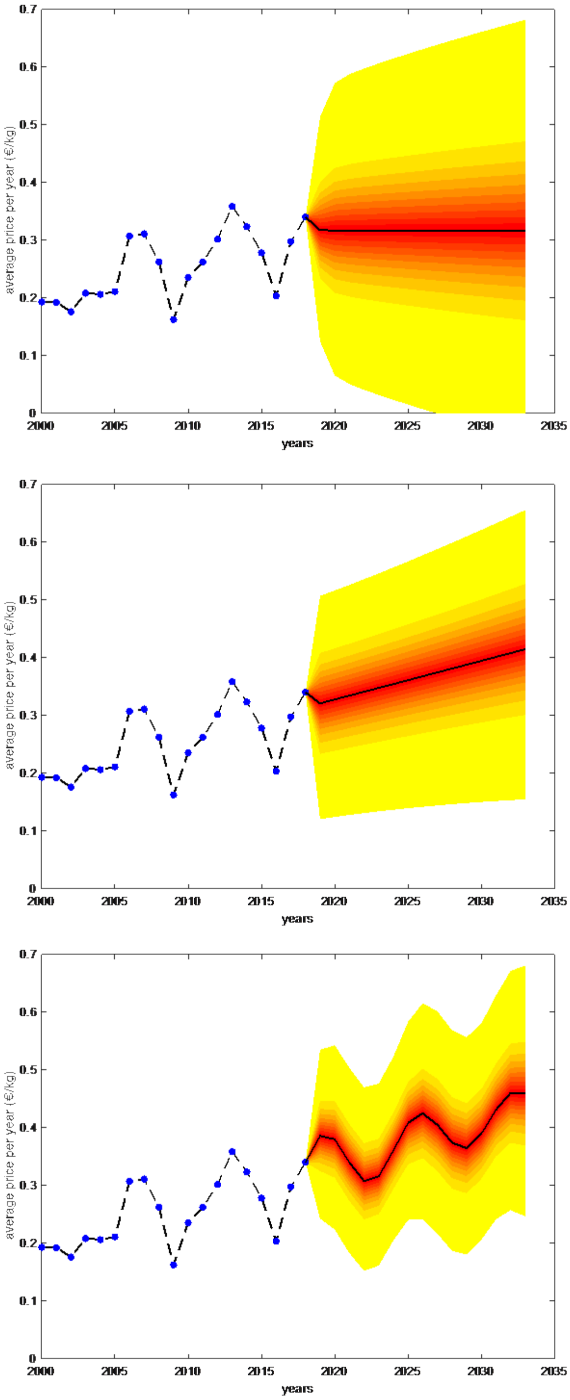

Figure 1. Yearly methanol price forecasts calculated by: a) DT model; b) LLT and c) LLTC.

Forecasts in Figure 1 shows two important aspects that previous works [2, 14, 17, 21-29] have not addressed. First, regardless of the forecasting model, since it is more difficult to predict the methanol price in 10 years ahead than next year, the prediction intervals widen as the forecasting horizon increases. Second, each time the forecasting model includes a component (trend or cycle) the intervals width is reduced. In other words, the damped trend model assume that the potential cycle is noise and, thus, the forecast intervals should cover those fluctuations and because of that, the forecasting intervals are wider. On the other hand, if those fluctuations are not noise but they can be considered as a structural component that will remain in the future, the LLT with cycle forecasting model produces a forecast with a cycle of the same frequency and with tighter prediction intervals.

In order to verify the adequacy of the forecasting models, Table 1 shows the Akaike Information Criterion (AIC) [44] and Bayesian Information Criterion (BIC) [45], which are typically used to balance the trade-off between the goodness of fit and simplicity of a particular model, where the lower the criterion value, the better. The idea behind these criteria is to minimize the risk of over and underfitting. Table 1 shows the AIC/BIC values for the three considered models in the hold-in sample. Considering both criteria, the lowest value is obtained by the LLTC, closely followed by the DT. Nonetheless, given the long forecasting horizon considered in this forecasting exercise and the close values of the criterion, it is extremely difficult to assure that the best performance obtained by the LLTC model will remain in the future and, thus, it is recommended to consider the three models for a correct evaluation of the future scenarios and let the managers decide which is more appropriate. In case we do not provide this information, the manager will decide with a myopic vision of the potential future scenarios. Therefore, hereafter, all the calculations will be assessed utilizing the three forecasting models.

Table 1. Information Criteria values for the considered forecasting models.

	DT	LLT	LLTC
AIC	11.45	11.85	11.43
BIC	11.91	12.78	11.87

3. Case study

3.1 Process description

The raw materials selected were olive pomace (op) from "*Aceites García de la Cruz*" olive oil mill, Madridejos (Toledo, Spain) and petcoke from a refinery of Puertollano (Ciudad Real, Spain) due to their abundance, their availability and their importance for Spanish society and economy. Aspen Plus® v9.0 was used to simulate the process of methanol shynthesis from biomass which has been evaluated economically herein. The design specifications for modelling the process and the validation have been published in previous studies [46]. Figure 2 shows the schematic diagram of the methanol production from syngas obtained through biomass gasification and Table 2 lists a brief explanation of the equipments used. The three main processes involved in the production of methanol from biomass are: gasification process, syngas cleaning and methanol synthesis. Firstly, the biomass is gasified at 900 ºC in a double chamber gasifier using steam as gasifying agent and a steam/biomass mass ratio of 0.9. This type of gasifier consists of a gasification and a combustion chamber. Thus, the main advantage of them, it is the possibility of generating all the energy needed for the gasification process in the combustion chamber through the char burning. Moreover, dolomite was used as the catalyst in order to decompose the tar produced. Then, the syngas produced was fed to the pressure swing adsorption (PSA) system to clean the syngas and capture the greenhouse gases. Finally, the purified was introduced to the methanol synthesis. The operating conditions for methanol synthesis were 220 ºC and 55 atm. In addition, due to the low conversions obtained in this process, Cu/ZnO was used as catalyst. Finally, in order to improve the system performance, the waste stream of methanol synthesis was recycled to the combustion chamber.

Table 2. Description of main equipment considered.

Equipment	**Description**
CT-01	Conveyor band
M-01	Ball mill
R-01	Gasifier
R-6	Methanol synthesis reactor
E-01	Heat exchanger
C-01	Two stage compressor
C-02	Two stage compressor
C-03	Single stage compressor
PSA-01	Separator to adsorb H_2
PSA-02	Separator to adsorb CO
PSA-03	Separator to adsorb CO_2
PSA-04	Separator to adsorb CH_4
E-02	Heat exchanger
METSEP	Separator of crude methanol

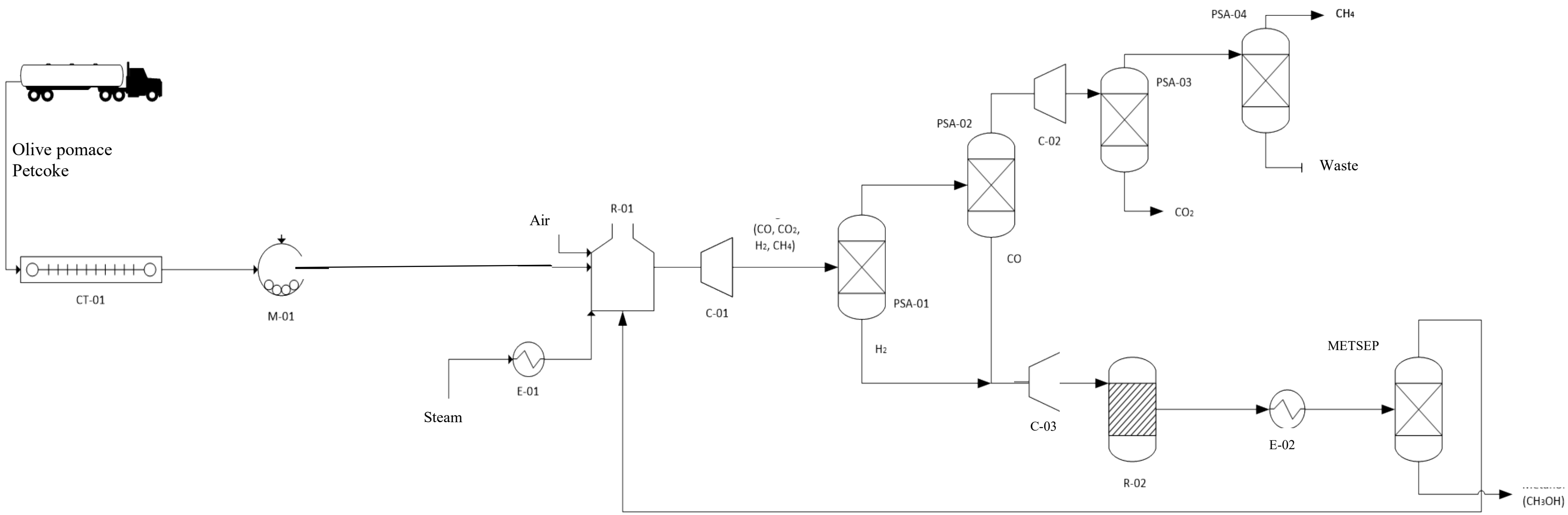

Figure 2. Schematic diagram of methanol production from biomass.

3.2 Economic aspects and metrics

The limiting factor for producing methanol from co-gasification of olive pomace and petcoke is the olive pomace amount due to it is a seasonal biomass which depends directly on the harvest. Thus, the production capacity of the plant was based on the amount of olive pomace fed. The 2015/16 harvest (due to it was one of the worst harvests in the last decade) and the hectares of Castilla-La Mancha and Andalucía regions were selected as the basis of calculation [30]. Using these data, the consumption of raw materials was 168,000 kg/h. At this point, two scenarios, whose main difference was the raw material used, were performed. Scenario 1 considered olive pomace as only raw material, and Scenario 2 considered a 75 wt. % of olive pomace and 25 wt. % of petcoke. The methanol yields obtained were 0.435 and 0.432 kg of methanol per kg of raw material for scenario 1 and 2, respectively. Table 3 summarizes the relevant economic parameters and assumptions considered in this study, such as the time period, the investment curve, the amortization and the discount rate which have been explained in detail in [30]. Note that the inflation was not included in the discount rate, it was considered separately. Finally, Net Present Value (NPV), Internal Rate of Return (IRR) and Value at Risk (VaR) were the investment criteria used for analysing the economic viability of the project.

Table 3. Relevant economic parameters and assumptions.

Main equipment cost	Aspen Process Economic Analyser® v9.0
Fixed capital investment[1]	Percentage of delivered equipment cost method
Working capital	20% of fixed capital investment
Operating time	8000 h
Time life	15 years
Investment curve	100 % Start-up
Amortization	Linear
Inflation rate[2]	2%
Discount rate[3]	10%

[1] [47, 48], [2] (es.inflation.eu) [3][23, 28, 49]

4. Uncertainty analysis

4.1 Deterministic case

First of all, a deterministic model for the financial evaluation of methanol production from biomass was carried out and tested, where its inputs were assumed to remain constant during the lifecycle of the plant. Table 4 depicts a summary of the fixed and working capital and annual operating costs for two evaluated scenarios. Besides, it can be observed that the cost of dolomite, catalyst and labor were considered the same for both scenarios, due to the fact that these costs depended solely on the plant capacity. For the same reason, the consumption of raw materials was the same for the two scenarios under study (168,000 kg/h). In this preliminary study, the static methanol price was considered of 0.36 €/kg [4].

Table 4. Operating annual costs for two scenarios and total capital cost for the deterministic model.

		Scenario 1 (Olive pomace)	**Scenario 2 (75op25P)**
	Price (€/kg)	**Cost (€/year)**	
Raw material			
Olive pomace	0.0077(1)	$10\cdot10^6$	$7.8\cdot10^6$
Petcoke	0.0709(2)	-	$24\cdot10^6$
Dolomite	0.2400(3)	$36\cdot10^3$	
Catalyst (Cu/Zn)	17.8(4)	$637\cdot10^3$	
Utilities		$86\cdot10^6$	$79\cdot10^6$
Labor cost		$945\cdot10^3$	$945\cdot10^3$
Other annual costs (indirect labor, maintenance, tax, laboratory…)		$22\cdot10^6$	$22\cdot10^6$
		Cost (M€)	
Fixed capital cost		175	
Working capital cost		35	

Total capital cost	**210**

[(1)]"*Aceites Garcia de la Cruz*" olive oil mill; [(2)] Refinery of Puertollano; [(3)] [50]; [(4)] [51], it is assumed that the lifetime of the catalysts are one year.

Considering all these costs (Table 4), the relevant economic parameters and assumptions (Table 3), and the constant price of methanol, the techno-economic parameters for analysing the economic viability of the present project was calculated. In this sense, Table 5 shows the main economic parameters (NPV and IRR) for both scenarios.

Table 5. Relevant economic parameters for both scenarios.

Scenario	*NPV (M€)*	*IRR (%)*
Olive pomace	339	30.51
75op25P	278	27.21

It can be observed that the NVP resulted positive for both scenarios, which confirms the economic viability. The IRR resulted to be 30.51 and 27.21 % for olive pomace and blend 75op25P, respectively, which also indicated the project profitability. Note that, these values of TIR were in the range of those reported by Andersson et al. [52], who carried out an economic analysis of methanol production via pressurized entrained flow biomass gasification. Finally, it can be concluded that the higher the olive pomace amount, the higher the profitability was. This is due the fact that the petcoke price is 9 times higher than the olive pomace.

Although this kind of determinist approach is appropriate as an initial estimation, if the main system variables are subject to uncertainty, as it occurs in this case study, neglecting them can significantly affect at the financial results and, thus, this simplistic estimation can lead to an incomplete evaluation. To overcome such issues, it is crucial to incorporate a risk analysis via Monte Carlo simulations, providing a stochastic perspective of the problem.

4.2 Partial uncertainty analysis. Methanol Price forecasting.

4.2.1 Monte Carlo simulations

This work proposes different econometric Unobserved Components models to enrich the Monte Carlo simulations with probabilistic forecasts of the methanol price. In this sense, probabilistic forecasts refer to the forecast of the whole predictive distribution of the methanol price, since it is more informative than a typical mean extrapolation. Those probabilistic forecasts will be fed into the Monte Carlo simulations with 10000 repetitions to project different economic scenarios.

4.2.2 NPV distribution

Figure 3 shows the probability distribution of the NPVs obtained as a result of Monte Carlo simulations for each scenario (Olive pomace and 75op25P) and forecasting model (DT, LLT and LLTC). Table 6 summarizes the main results using some well-known statistics. Taking into account the assumed scenarios, the NPV mode and mean obtained from olive pomace was higher than the sample 75op25P in all models used. Besides, this difference between them was similar for the three model forecasts. In addition, mean NPV was positive for all cases considered, but NPV value was influenced by the different model forecasts, being the most optimistic model the Local Linear Trend, and the most pessimistic model the damped trend. That figure also shows as a vertical dotted line (DC) the results obtained by the determinist case. It can be observed how the deterministic case overestimates the NPV mean and it does not provide any information about the investment risk, in contrast to the histograms obtained from the Monte Carlo simulations.

Note that, since the NPV distributions were practically symmetric, the mode and mean were similar. Table 6 also shows the maximum and minimum value of NPV for each scenario and model. In general, the dipersion of the NPV results can be measured by the rank (the difference between maximum and minimum) and the standard deviation. Essentially, the LLT model presents the lowest dispersion since it incorporates the positive trend and, thus, it reduces the variability unexplained by the model. The dispersion of the LLTC model is higher due to the variability introduced by the cycle.

In order to evaluate the investment risk, the Value at Risk (Var), which is the probability that the NPV was less than zero, was calculated using the histograms in Figure 3. Table 6 shows the VaR for each combination of Scenario and model. It can be observed that the probability of obtaining a positive NPV result for olive pomace was higher than for the 75op25P sample given that the VaR was lower. Interestingly, the VaR was much lower considering the Local Linear trend, which was practically zero. These results were in accordance with the different NPV values aforementioned. Moreover, it can be seen that the difference between VaR of olive pomace and 75op25P also decreased considerably using this model.

These results indicate that there is a high probability for the plant to be profitable despite the volatility of methanol prices.

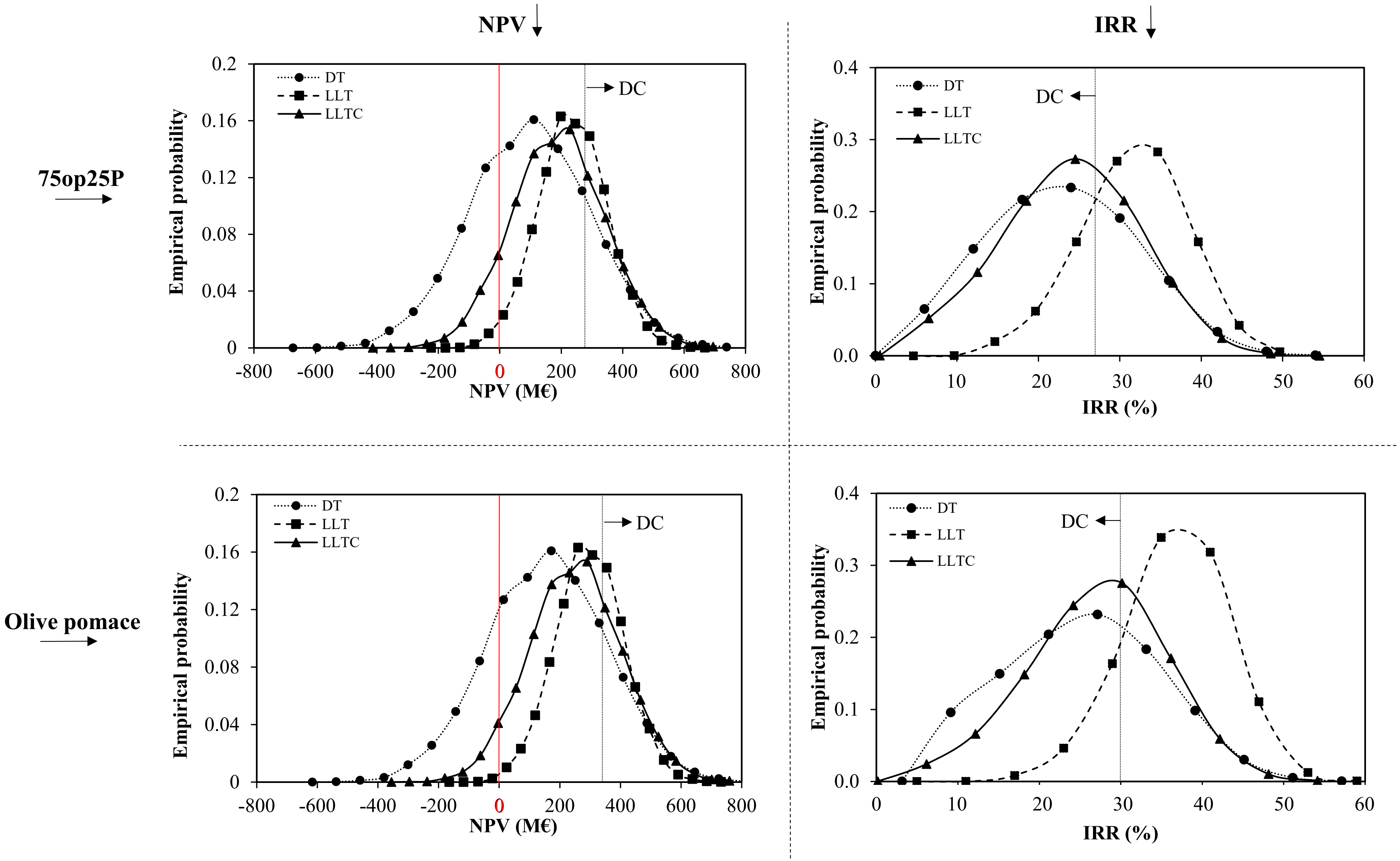

Figure 3. NPV and IRR histograms. Upper panels: 75op25P. Lower panels: Olive pomace. Left panel: NPV. Right panel: IRR. DT, LLT and LLTC are the considered forecasting models. DC corresponds to the deterministic case results.

4.2.3 IRR distribution

Right panel in Figure 3 shows the probability distribution of the IRRs obtained as a result of Monte Carlo simulations for each scenario and model as well as the deterministc case. Table 7 summarizes the main results. The results obtained presented a similar trend to NPV distributions. Thus, IRR mode and mean obtained from olive pomace was higher than the sample 75op25P regardless of the forecasting model. In addition, mean IRR was higher than the discount rate for all experiments considered showing evidence of the profitability of the investment. Regarding the deterministic case, it lies between the IRR mean obtained by the LLT and LLTC forecasting models.

As occurred when assessing the NPV, IRR was influenced by the different forecasting models. Concerning maximum value of IRR it can be observed that the highest value was for DT model. Note that, those repetitions where the IRR could not be calculated, because of numerial issues due to negative NPV, were not considered in the histograms. Regarding standard deviation, it was similar for the samples 75op25P and olive pomace for all the forecasting models considered, as it occurred with the NPV distributions. Similarly, LLT model presented the lowest standard deviation.

Table 6. Summary of NPV results for each scenario and forecasting model.

	Damped Trend		*Local Linear Trend*		*Local Linear Trend with cycle*	
	Olive pomace	**75op25P**	**Olive pomace**	**75op25P**	**Olive pomace**	**75op25P**
Mode NPV (M€)	172	111	260	198	290	228
Mean NPV (M€)	158	97	298	236	252	190
Maximum (M€)	891	816	732	667	758	693
Minimum (M€)	-617	-673	-165	-224	-356	-413
Deviation	197	195	112	112	152	151
VaR (%)	18	30	0	1	7	14

Table 7. Summary of IRR results for each scenario and forecasting model.

	Damped Trend		*Local Linear Trend*		*Local Linear Trend with cycle*	
	Olive pomace	**75op25P**	**Olive pomace**	**75op25P**	**Olive pomace**	**75op25P**
Mode IRR (%)	27	24	29	28	30	25
Mean IRR (%)	25	23	31	27	27	24
Maximum (M€)	56	53	51	48	51	48
Minimum (M€)	0	0	0	0	0	0
Deviation (%)	9	9	6	7	8	8

4.3 Complete uncertainty analysis

4.3.1 Monte Carlo simulations

Besides the methanol price, other sources of uncertainty to be included in the Monte Carlo simulations are the olive pomace feed, capital investment, feedstock price, labor costs and discount rate. For these variables, the extent of uncertainty are modeled simulating a triangular distribution [23]. Table 8 shows the value and their ranges considered. Note that a triangular distribution is a continuous probability distribution that is defined by three values: the minimum value, the maximum value, and the peak value [23]. This is commonly used in a real-life situation given that it is possible to estimate the maximum, minimum, and the most likely outcome [53]. Note that, for those variables a forecasting exercise cannot be implemented, as it happened with the methanol price, due to the limited past information available.

Table 8. Summary of variables with uncertainty distributions.

Variable	***Minimum Value***	***Expected Value***	***Maximum Value***	***Distribution***
Olive pomace feed (kg/h)	-50 %	168 000	0 %	Triangular
Olive pomace price (€)	0.0062	0.0077	0.0154	Triangular
Petcoke price (€)	0.0355	0.0709	0.1064	Triangular
Total Capital Investment (M€)	−30%	210	+100%	Triangular
Labor costs (€)	−20%	945 000	+20%	Triangular
Discount rate (%)	4	10	16	Triangular

Concerning the uncertain variables, olive pomace feed was considered due to the fact that is a seasonal biomass that depends directly on the harvest. Therefore, the production capacity of the plant was based on the amount of olive pomace fed. The 2015/16 harvest and the hectares of Castilla-La Mancha and Andalucía regions were selected as the basis of calculation. The consumption of raw materials was 168, 000 kg/h. Moreover, methanol production was directly affected by its variation. The minimum value was obtained taking in account the worst harvest registered in the recent years [data from Aceites García de la Cruz Olive Oil mill] and the expected and maximum value was equal to the plant capacity. In the case of Scenario 2, the petcoke feed was also altered.

The raw material cost can vary widely depending on geographic and environmental factors or costs associated with harvesting and transportation. In reference to olive pomace price, the expected value was obtained from Aceites García de la Cruz olive oil mill, and the maximum and minimum value was acquired from different databases of olive oil sector [54]. For petcoke price, it can be observed that is one order of magnitude higher than the olive pomace price. Table 4 also shows the total annual cost of raw materials for the deterministic model. Note the importance of the Petcoke in cost terms, for the Scenario 2 (75op25P), where the Petcoke implied, approximately, the 75% of the total raw material cost. The expected value was obtained from the refinery of Puertollano. As aforementioned, the petcoke cost can vary depending on geography and quality factors. Therefore, the minimum and maximum value considered an uncertain distribution ranging from ± 50% in order to reflect different petcoke qualities.

Total capital investment was difficult to estimate for the percentage of delivered equipment cost method applied. Besides, this method is based on the main equipment prices which were obtained from Aspen Plus v.9 and they can be overestimated or underestimated. For that reason, distribution ranging from - 30% +100% was considered since estimations are more likely to be understimated compared to actual project costs [55].

For its part, the labor cost distribution can vary depending on the regions and can be increased or decreased from one year to the next due to the social and global political changes, so the range of labor cost was estimated ± 20% [23]. Finally, the discount rate was varied between 4 and 16% [23]. This variable includes a risk premium due to the risk inherent with novel technologies, which can vary with the riskiness of the investment.

4.3.2 NPV distribution

Figure 4 displays the probability distribution of the NPVs obtained as a result of Monte Carlo simulations for each scenario and model taking into account all uncertain variables. Table 9 lists the main statistics results. It can be observed that NPV mode and mean were negative for both raw materials, being the results worse in the case of 75op25P. It can be attributed to the larger number of variables involved in the case of 75op25P. In this sample, there were two more variables involved besides the olive pomace, particularly, the price of petcoke (which was not considered for olive pomace) and the petcoke feed. In addition, it is important to note that the higher the petcoke flow, the lower the methanol production. Therefore, this last variable also indirectly affected the results obtained, being the risk assumed for 75op25P much higher. As was observed in the previous section, NPV value was influenced by the different model forecasts, being LLT the most optimistic model. Moreover, NPV values obtained including all sources of uncertainty were lower than the deterministic method and the methanol price forecasts as the single source of uncertainty case, due to the increased risk considered.

Regarding NPV distributions, the mode and the mean were similar as a consequency of symmetric distribution. On the other hand, the maximum value of NPV presented higher differences between the olive pomace and 75op25P than the case of partial uncertainty analysis. However, the variance of minimum value was not as high as the maximum value. Comparing the three models, in general terms, similar conclusions can be drawn with respect to the preceding section. Concerning standard deviation, it was different for the scenarios and model forecasts considered. Nonetheless, LLT model presented the lowest standard deviation. Regarding the VaR, it can be observed that the probability of obtaining a positive NPV result for 75op25P was quite low, given that the VaR is high, while the olive pomace presented a probability close to 50 % for LLT and LLTC models. Therefore, these results show that for both scenarios, apart from reducing the profitability in general terms, the investment risk measured by VaR was dramatically increased.

Note that, the NPV values in Figure 4 are frequently negative, particularly for the 75op25P case. Therefore, the IRR empirical probability plots are not shown because in many cases the numerical solutions of IRR do not converge and, thus, its interpretation can be misleading.

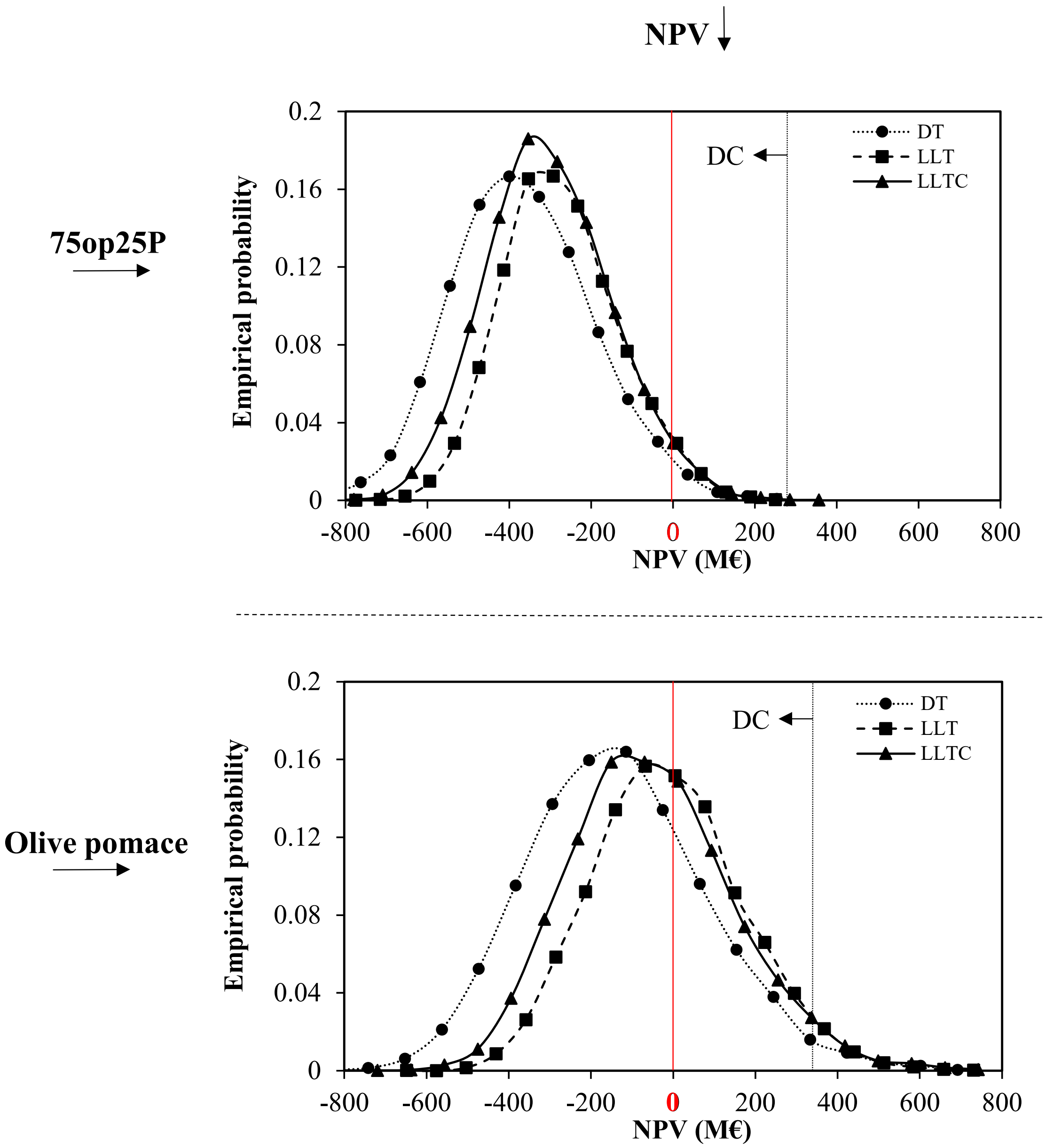

Figure 4. NPV histograms. Upper panels: 75op25P. Lower panels: Olive pomace. DT, LLT and LLTC are the considered forecasting models. DC corresponds to the deterministic case results.

Table 9. Summary of NPV results each scenario and forecasting model.

	Damped Trend		***Local Linear Trend***		***Local Linear Trend with cycle***	
	Olive pomace	**75op25P**	**Olive pomace**	**75op25P**	**Olive pomace**	**75op25P**
Mode NPV (M€)	-115	-400	-68	-292	-151	-353
Mean NPV (M€)	-136	-368	-13	-275	-51	-302
Maximum (M€)	780	325	730	249	740	356
Minimum (M€)	-921	-1053	-649	-895	-800	-992
Deviation	219	172	184	142	199	153
VaR (%)	77	98	48	95	57	95

5. Conclusions

The financial viability of methanol production from biomass gasification was carried out by means of deterministic and stochastic methods. In order to assure a stable production of methanol regardless the size of the olive harvest, two scenarios were considered: olive pomace and blend 75op25P (75 wt. % of olive pomace and 25wt.% of petcoke). A deterministic model was developed as a benchmark, observing that NPV was positive for both scenarios. The IRR was 30.51 and 27.21 % for olive pomace and blend 75op25P, respectively.

To complete the deterministic study, a stochastic perspective was incorporated by analysing the investment risk. The first approximation of the stochastic analysis investigated the influence of the methanol price volatility. In this sense, three Unobserved Components forecasting models set in a State Space framework were analysed. Such models were designed to include trend (Damped Trend and Local Linear Trend) and cycle (Local Linear Trend with Cycle) components identifiable in the methanol price time series. All investment criteria indicated that using olive pomace as a single feedstock was more profitable than the sample 75op25P independently of the forecasting model used. Additionally, the risk of the investment was supported by the low values of the Value at Risk metric. The IRR values ranged from 23% for the 75op25P scenario and DT forecasting model to 31% for the Olive pomace scenario and LLT model. In general terms, the Local Linear Trend model presented the most optimistic results in economic terms, since that model assumes that the methanol price, which is the main variable driving revenues, has a positive trend and, thus, provides higher methanols prices.

Finally, the stochastic exercise was completed by including the rest of variables subject to uncertainty (olive pomace feed, capital investment, feedstock price, labor costs and discount rate). In this case, the probability of obtaining a positive NPV result for 75op25P was between 2% and 5%, while olive pomace presented a probability around 48% and 77% depending on the forecasting model, being the Local Linear Trend again, the model that yielded the most optimistic NPV values.

Among the results of this work, an important conclusion achieved is the need to carry out a stochastic analysis of the economic assessment when certain variables of the study are subject to uncertainty, in contrast to the simple deterministic approach, which unrealistically assumes that the future value of all variables are known with certainty.

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