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Integrated production-distribution scheduling with energy considerations for efficient food supply chains

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Abstract

Quantitative approaches for the integration of production and distribution planning are attracting the interest of scholars and companies in recent years. They can significantly improve supply chain performance and sustainability. In this paper, we propose an optimization model for the integrated scheduling of production and distribution activities, with reference to a real-life company in the food sector. The model takes into consideration changeover times and perishability, and aims to jointly minimize energy, storage and distribution costs. Its applicability is shown through a set of computational experiments, carried out on instances generated from historical data. Two different rescheduling strategies, where the first one reproduces the current behaviour of the firm, are compared. The results show that the current practices of the company can be improved and the model is a valid tool for supporting operational business decisions.

Keywords: Food supply chain; production scheduling; inventory management; distribution; energy-efficient

1. Introduction

Quantitative approaches for the integration of production and distribution planning in the supply chain are attracting the interest of scholars and companies in recent years [1]. In the past, there was the tendency to optimize locally every single stage of the supply chain. Recently, instead, research has been moving towards integrated approaches, with the aim to effectively deal with frequent market changes, customer needs, uncertainty [2]. Specifically, if we refer to the food sector, supply chain management is even more complex as it is necessary to take into account additional features such as food quality and safety [3, 4], and raw material, semifinished and finished product perishability [5]. Considering the expected increase in food demand in the next years, it is crucial to protect sustainability and minimizing food waste. In this challenging context, production systems need to be efficiently managed, especially

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because energy cost is rising due to the considerable grow of energy demand in the last few years. In fact, the efficient use of energy resources leads to cost savings and reduction in greenhouse gas emissions [6].

Therefore, the aim of this paper is to develop and test an optimization model to determine in an integrated manner the production and delivery plan for a company, which operates in the food sector. Energy, inventory and distribution costs are jointly minimized. Two production (re)scheduling strategies [7] are compared, where the first one reproduces the current behaviour of the company.

The remainder of the paper is organized as follows. Section 2 collects the main contributions in the literature about energy-efficient scheduling models, and integrated production-distribution approaches in the food supply chain. In Section 3, we present our optimization model to support the decision-making of a company operating in the food sector. Section 4 contains the computational experience on a real-life case study. In Section 5, we outline conclusions and some possible future developments.

2. Literature review

Considering the topic of this paper, we divide our literature review into two main parts. The former collects energy-efficient scheduling models, while the latter concerns the coordination of production and distribution activities in the food supply chain.

2.1. Energy-efficient scheduling models

Electricity prices are extremely variable. Power suppliers usually charge higher electricity prices at peak hours, while more reasonable prices are proposed during mid-peak or off-peak hours [8]. Through an efficient scheduling of production activities, it is possible to save on energy costs by limiting the activities carried out during peak hours. In the following, we review the most relevant energy-efficient scheduling models based on the policy of time-of-use (TOU) electricity tariffs. We focus our attention only on papers which tackle single-machine and/or food-related problems.

A mathematical model to minimize energy consumption costs with reference to a single machine is proposed in [9]. The framework takes into consideration the fluctuations in energy prices, and multiple machine states with own energy consumption: turning on, turning off, idle. Given the model complexity, a genetic algorithm is proposed to solve it. The authors show that heuristic solutions are preferable, especially when the size of the problem is considerable. The mathematical formulation proposed in [9] is improved in [10], with the aim to reduce the number of decision variables and make less time-consuming the problem. A mixed integer linear programming (MILP) model is presented in [11] to optimize the operations of a real-world food production plant characterized by several production lines and product types. The aim is to minimize the total manufacturing cost, represented by electricity consumption and labor. An integer linear programming model (ILP) is designed in [12] to address a real-life problem with reference to a Portuguese food retail company. The main goal is to minimize the energy-cost for the production of flake ice, which is very important to preserve fish freshness in food retail stores. The proposed model, tested both on real and randomly generated instances, suggests the production of the best amount of ice at the right time, minimizing waste. The overall results show that it is possible to achieve an average annual saving greater than 30%.

Several research works aim to jointly minimize two specific objectives, namely makespan and total energy costs. An integer programming model is presented in [13] to tackle a single-machine batch scheduling problem with non-identical job sizes. An ϵ-constraint method and two decomposition-based heuristic approaches are used to solve it. The computational experiments show the applicability of the proposed methods. An MILP model is instead proposed in [14] to address a single-machine batch scheduling problem with machine on/off switching and TOU tariffs. A heuristic based ϵ-constraint method is designed to solve efficiently the problem, especially the largest instances. An integrated production scheduling and maintenance planning problem under TOU tariffs is addressed in [15]. In this case, the two objectives (i.e., makespan and total energy costs) measure respectively the service level and energy sustainability. The problem is solved through a heuristic framework, characterized by two different layers. The first one (i.e., the inner) is based on a Branch & Bound algorithm, and optimizes the maintenance decisions. The second one (i.e., the outer) refers to production scheduling and is solved by a hybrid NSGA-II algorithm. The Pareto frontier is used as a tool for supporting the decision-maker.

We point out that more detailed information about decision support systems for energy-efficient production planning can be found in some recent and comprehensive surveys [16, 6].

2.2. Integrated production scheduling and distribution planning in the food supply chain

By coordinating production and distribution activities, it is possible to achieve a reduction in total operating costs between 3% and 20% [17]. In the following, we review the most relevant papers, in which the integration of production scheduling and distribution planning, with reference to the food supply chain, is tackled.

The short production scheduling and distribution planning problem within the dairy industry is addressed in [18]. The authors develop an MILP model, which takes into account many real-life features such as sequence-dependent setup times, machine speeds, overtime, minumum and maximum lot-size, shelf life constraints. A hybrid methodology, based on the MILP formulation and a simulation approach, is designed to obtain the optimal production and delivery plan. A case study referring to a company located in Turkey shows the goodness of the proposed approach. A non linear mathematical model is proposed in [19] to simultaneously optimize production scheduling and vehicle routing with time windows in the case of perishable food products. The main features of the model are (i) customer demand stochasticity and (ii) finished products deterioration. The goal is the maximization of the expected total profit. Since the problem is computationally complex, a solution algorithm is developed, with good results. A framework for the integrated production-distribution planning problem, referring to multi-product and semi-continuous food processing industries, is proposed in [20]. Changeover times between different product families are explicitly taken into account, and several transportation modes for the deliveries to the customers are compared. The efficiency of the designed approach is demonstrated through two industrial case studies, related to the yogurt sector in Greece. In [21], a mixed integer programming model is used to formulate the single plant, integrated production and distribution scheduling problem. The peculiarity is the perishable nature of the products, which significantly influences the delivery plan. Evolutionary approaches are developed and used to find good solutions for the problem, in reasonable time. The work is an extension of [22]. The operational integrated production and distribution planning problem with perishable products is addressed in [23]. The main decisions concern line-assignment, lot-sizing/splitting, vehicle routing. The proposed adaptive large neighborhood search (ALNS) framework is very efficient and outperforms the traditional methods (i.e., exact methods, fix-and-optimize) in solving the problem.

More detailed informtion about integrated production-distribution models can be found in some comprehensive surveys [1, 2].

3. Problem description and mathematical model

We refer to a make-to-order company, which deals with production, storage and distribution of food products along a discrete time horizon $\mathcal{D} = \{1, \ldots, D\}$. Each day of the time horizon is denoted by $d \in \mathcal{D}$ and is divided into a set $\mathcal{S}$ of slots of equal time length. The firm has a single production line and deals with a set $\mathcal{P}$ of products, whose a subset $\overline{\mathcal{P}}$ is characterized by highly perishable raw materials, which have a maximum storage time τ_p. We denote by α_p and r_p, respectively, the amount of energy consumption and the capacity of the line per slot, when product p is manufactured. The production line has a product setup β at the beginning of the planning horizon. The energy cost is subject to fluctuations throughout the day, then we denote by λ_{sd} the energy price at slot s of day d. Once manufactured and before being delivered, the products are stored in the inventory, which has a capacity I_{max}. We denote by h_p the daily unit storage cost referring to product p. Along the time horizon, C customers have to be served. K vehicles are available for the shipping stage, each having a load capacity l_k. An amount of θ_c shipments has to be guaranteed to customer c for each week w of the time horizon. We denote by dem_{pcw} the demand of product p by customer c at week w, while γ_c^k is the cost for serving customer c by vehicle k. Deliveries are not allowed on some days $d \in \widetilde{\mathcal{D}}$. In Table 1, the notation of all problem data is shown.

The goal is to simultaneously minimize energy, storage, and distribution costs. For what concerns the production phase, the decisions to be daily made regard the amount Q_{psd} of product p manufactured at each slot s. In addition, the functioning of the single line is regulated by binary variables x_{psd} and y_{psd}, which define the set up and production type at each slot s of day d, respectively. Setups are also managed by binary variables $\delta_{pp'sd}$, which are active in case a changeover from product p to p' occurs at slot s of day d. The inventory management is guaranteed by variables I_{pd},

Table 1. Notation: problem data

$\mathcal{D}$	set of days of the time horizon, with $\mathcal{D} = \{1, \ldots, D\}$;
$\widetilde{\mathcal{D}} \subset \mathcal{D}$	set of days of the time horizon on which deliveries are not allowed;
$\mathcal{W}$	set of weeks of the time horizon, with $\mathcal{W} = \{1, \ldots, W\}$;
$\overline{\mathcal{D}}_w$	set of days of week w;
$\mathcal{P}$	set of products, with $\mathcal{P} = \{1, \ldots, P\}$;
$\overline{\mathcal{P}} \subset \mathcal{P}$	set of products, whose raw materials are highly perishable;
$\mathcal{S}$	set of working slots per day, with $\mathcal{S} = \{1, \ldots, S\}$;
C	set of customers, with $C = \{1, \ldots, C\}$;
$\mathcal{K}$	set of vehicles, with $\mathcal{K} = \{1, \ldots, K\}$;
α_p	amount of energy consumption per slot in case product p is produced;
r_p	production capacity referring to product p per slot;
β	initial product setup on the line;
τ_p	maximum storage time of highly perishable raw materials with reference to product $p \in \overline{\mathcal{P}}$;
λ_{sd}	energy price at slot s of day d;
h_p	daily unit storage cost of product p;
I_{max}	storage capacity;
dem_{pcw}	demand of product p expressed by customer c at the beginning of week w;
l_k	load capacity of vehicle k;
γ_c^k	shipping cost for customer c with vehicle k;
θ_c	fixed number of weekly shipments for customer c.

which define the inventory level of product p at the end of day d. About the distribution stage, variables w_{dc}^k define whether or not to use vehicle k to serve customer c at day d, while the amount of product p shipped to customer c by vehicle k at day d is defined by continuous variables z_{pdc}^k. The notation of the decision variables of our optimization model is shown in Table 2.

Table 2. Notation: decision variables

x_{psd}	binary variable equal to one if production line is set up for product p in slot s of day d;
$\delta_{pp'sd}$	binary variable equal to one if a changeover from product p to p' takes place in slot s of day d;
y_{psd}	binary variable equal to one if there is production of product p in slot s of day d;
I_{pd}	inventory level of product p at the end of day d;
Q_{psd}	amount of product p produced at slot s of day d;
w_{dc}^k	binary variable equal to one if customer c is served by vehicle k at day d;
z_{pdc}^k	amount of product p shipped to customer c by vehicle k at day d.

In the following, we introduce the model formulation.

$$\min \quad \sum_{p\in\mathcal{P}}\sum_{s\in\mathcal{S}}\sum_{d\in\mathcal{D}}\lambda_{sd}\alpha_p y_{psd} + \sum_{p\in\mathcal{P}}\sum_{d\in\mathcal{D}} h_p I_{pd} + \sum_{k\in\mathcal{K}}\sum_{d\in\mathcal{D}}\sum_{c\in\mathcal{C}}\gamma_c^k w_{dc}^k \tag{1}$$

$$\sum_{p\in\mathcal{P}} x_{psd} = 1 \qquad s\in\mathcal{S}, d\in\mathcal{D} \tag{2}$$

$$y_{psd} \le x_{psd} \qquad p\in\mathcal{P}, s\in\mathcal{S}, d\in\mathcal{D} \tag{3}$$

$$Q_{psd} \le r_p y_{psd} \qquad p\in\mathcal{P}, s\in\mathcal{S}, d\in\mathcal{D} \tag{4}$$

$$\delta_{\beta p'11} \ge x_{p'11} \qquad p'\in\mathcal{P} : \beta \ne p' \tag{5}$$

$$\delta_{pp'sd} \ge x_{ps-1d} + x_{p'sd} - 1 \qquad p,p'\in\mathcal{P} : p\ne p', s\in\mathcal{S}\setminus\{1\}, d\in\mathcal{D} \tag{6}$$

$$\delta_{pp'1d} \ge x_{pSd-1} + x_{p'1d} - 1 \qquad p,p'\in\mathcal{P} : p\ne p', d\in\mathcal{D}\setminus\{1\} \tag{7}$$

$$1 - y_{p'sd} \ge \delta_{pp'sd} \qquad p,p'\in\mathcal{P} : p\ne p', s\in\mathcal{S}, d\in\mathcal{D} \tag{8}$$

$$\sum_{s\in\mathcal{S}}\sum_{d\in\overline{\mathcal{D}}_w : d\le\tau_p} Q_{psd} = \sum_{c\in\mathcal{C}} dem_{pcw} \qquad p\in\overline{\mathcal{P}}, w\in\mathcal{W} \tag{9}$$

$$\sum_{k\in\mathcal{K}}\sum_{d\in\overline{\mathcal{D}}_w\bigcup\overline{\mathcal{D}}_{w+1}} z_{pdc}^k \ge dem_{pcw} \qquad p\in\mathcal{P}, c\in\mathcal{C}, w\in\mathcal{W}\setminus\{W\} \tag{10}$$

$$\sum_{k\in\mathcal{K}}\sum_{d\in\overline{\mathcal{D}}_W} z_{pdc}^k = dem_{pcW} \qquad p\in\mathcal{P}, c\in\mathcal{C} \tag{11}$$

$$\sum_{k\in\mathcal{K}}\sum_{d\in\mathcal{D}} z_{pdc}^k = \sum_{w\in\mathcal{W}} dem_{pcw} \qquad p\in\mathcal{P}, c\in\mathcal{C} \tag{12}$$

$$\sum_{c\in\mathcal{C}} w_{dc}^k \le 1 \qquad k\in\mathcal{K}, d\in\mathcal{D} \tag{13}$$

$$\sum_{p\in\mathcal{P}} z_{pdc}^k \le l_k w_{dc}^k \qquad k\in\mathcal{K}, d\in\mathcal{D}, c\in\mathcal{C} \tag{14}$$

$$\sum_{p\in\mathcal{P}} I_{pd} \le I_{max} \qquad d\in\mathcal{D} \tag{15}$$

$$I_{p0} = 0 \qquad p\in\mathcal{P} \tag{16}$$

$$I_{pd} = I_{pd-1} + \sum_{s\in\mathcal{S}} Q_{psd} - \sum_{c\in\mathcal{C}}\sum_{k\in\mathcal{K}} z_{pdc}^k \qquad p\in\mathcal{P}, d\in\mathcal{D} \tag{17}$$

$$\sum_{k\in\mathcal{K}}\sum_{c\in\mathcal{C}} z_{pdc}^k \le I_{pd-1} \qquad p\in\mathcal{P}, d\in\mathcal{D} \tag{18}$$

$$\sum_{d\in\overline{\mathcal{D}}_w}\sum_{k\in\mathcal{K}} w_{dc}^k = \theta_c \qquad c\in\mathcal{C}, w\in\mathcal{W} \tag{19}$$

$$\sum_{k\in\mathcal{K}}\sum_{c\in\mathcal{C}} w_{dc}^k = 0 \qquad d\in\widetilde{\mathcal{D}} \tag{20}$$

$$y_{psd}, x_{psd} \in \{0,1\} \qquad p\in\mathcal{P}, s\in\mathcal{S}, d\in\mathcal{D} \tag{21}$$

$$\delta_{pp'sd} \in \{0,1\} \qquad p,p'\in\mathcal{P} : p\ne p', s\in\mathcal{S}, d\in\mathcal{D} \tag{22}$$

$$I_{pd} \ge 0 \qquad p\in\mathcal{P}, d\in\mathcal{D}\cup\{0\} \tag{23}$$

$$Q_{psd} \ge 0 \qquad p\in\mathcal{P}, s\in\mathcal{S}, d\in\mathcal{D} \tag{24}$$

$$w_{dc}^k \in \{0,1\} \qquad d\in\mathcal{D}, c\in\mathcal{C}, k\in\mathcal{K} \tag{25}$$

$$z_{pdc}^k \ge 0 \qquad p\in\mathcal{P}, d\in\mathcal{D}, c\in\mathcal{C}, k\in\mathcal{K} \tag{26}$$

The objective function (1) minimizes the total costs. The three terms refer to energy, inventory, and shipping costs, respectively. Constraints (2) state that the production line must be set up for exactly one product at each time. However, due to constraints (3), such a set-up does not necessarily follow an actual production. Constraints (4) limit the production capacity of the line. Constraints (5)-(8) regulate the changeovers on the production line. Constraints (9) take into account the perishability of raw materials. Constraints (10)-(11) define the time horizon within which the demand of each customer must be met. While, constraints (12) ensure that demand equals the total amount of shipped products, over the planning horizon. Constraints (13) state that each vehicle can serve not more than one customer per day. Constraints (14) ensure that the load capacity of each vehicle is not exceeded at each day. Constraints (15)-(17) regulate the inbound/outbound mechanism of product to/from the inventory, considering its limited capacity and assumed initial null level. Constraints (18) state that only products in stock at the beginning of each day can be shipped to the customers. Constraints (19) establish the number of weekly shipments for each customer. Constraints (20) prevent deliveries on some days. Constraints (21)-(26) define the nature of the decision variables.

4. Case study

We consider a real-life case study to prove usufulness and efficiency of the proposed optimization model. We refer to an Italian company that deals with the production, storage and distribution of vegetables. Basically, six types of product are produced ($p_1, p_2, ..., p_6$). One production line is available and can be set up for one product type at a time both for hygiene reasons and above all because each product type requires its own process parameters. According to the historical data provided by the company, the average changeover time is one hour. Energy consumption of the line varies according to the products processed. Most of the raw materials useful to feed the production cycle are sent directly by the customers for quality reasons. Therefore, the company of our case study transforms and sends them back to customers/suppliers in the form of finished products. Customers, who are wholesalers within the overall food supply chain, express their demand at the beginning of each week and jointly make raw material available. Such demand must be satisfied within two weeks as the products must be placed on the shelves of the retailers in time for the planned promotional offers. It should be noted that as regards p_5 and p_6, the relative raw material is highly perishable then it must necessarily be processed within seven days. The company works on two daily shifts of 8 hours each. After the production process, the finished products, before being be shipped, must be stored in the inventory, whose capacity is 20,000 units. The storage cost concerns maintaining the temperature level to preserve food quality.

For what concerns the distribution phase, two vehicles are available with load capacity of 10,000 units and 3,000 units, respectively. According to the contractual agreements, each customer must be served twice a week. Considering the different geographical positioning of the customers and the different vehicles size, the shipping cost depends on the customer to be served and the vehicle used. In any case, each vehicle can serve at most one customer per day.

4.1. Instances

We refer to a time horizon of eight weeks between February and March, which is one the most challenging period in terms of amount produced and distributed. During the considered time interval, the amount produced is usually around 60,000 units.

With the aim to address the problem under multiple realistic scenarios, we have generated 10 instances. In particular, we have generated the following data, by using a normal distribution with coefficient of variation equal to 0.05: λ_{sd}, dem_{pcw}. The energy price has been estimated from the historical data made available by Gestore dei mercati energetici (GME) [24], which is the company responsible in Italy for the organization and management of the electricity market. In Figure 1, we show the energy price trend on a generic day of the time horizon, during the working hours of the company (i.e., 8h00-24h00). In particular, the black line refers to the historical data, while the grey one concerns the generated data. For what regards the mean of the weekly demand of each product type by each customer, it has been estimated considering the historical data provided by the company.

In Tables 3-4, we summarize the relevant data, referring to the current operating conditions of the firm.

The computational experiments have been carried out on a PC running Windows 10 Pro with AMD Ryzen 7 2700X Eight-Core Processor 4.00 GHz/16GB. The presented optimization model has been solved by CPLEX 12.7, Academic License.

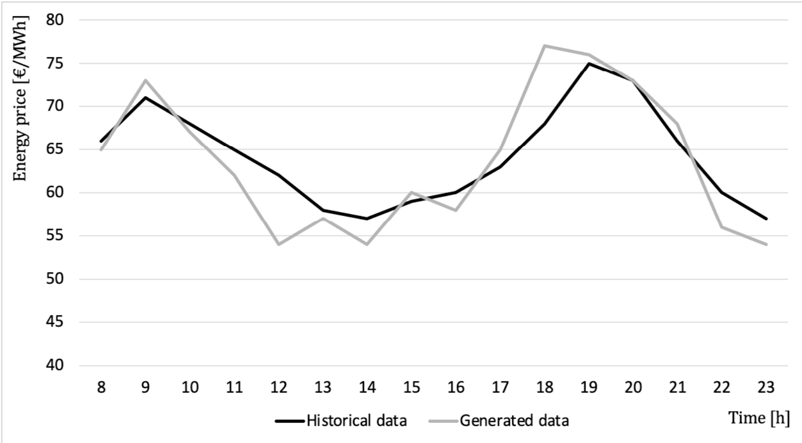

Fig. 1. Energy price trend on a generic day of the time horizon: historical data vs. generated data

Table 3. Case study: product data

	p_1	p_2	p_3	p_4	p_5	p_6
r_p [unit/hour]	200	285	750	375	185	185
α_p [kWh]	25	22	21	18	12	13
h_p [€/unit]	0.05	0.04	0.05	0.03	0.08	0.08

Table 4. Case study: other relevant data

C	K	l_1	l_2	I_{max}	γ_1^1,γ_1^2	γ_2^1, γ_2^2	θ_1, θ_2
[unit]	[unit]	[unit]	[unit]	[unit]	[€/shipment]	[€/shipment]	[unit]
2	2	10,000	3,000	20,000	200, 150	120, 80	2

4.2. Rescheduling strategies and computational results

We have adopted our model with the aim to improve the current practices of the company. In particular, we have implemented and compared two different strategies, named respectively partial rescheduling (PR) and complete rescheduling (CR), within a rolling horizon scheme. It should be noted that the first strategy reproduces the current behaviour of the company. In Figure 2, we show the rolling horizon scheme.

Basically, given an overall time horizon of n weeks, $(n-1)$ iterations are necessary to solve the problem. In fact, at each iteration, the optimization model is solved considering a bi-weekly planning horizon. The first iteration concerns the first and second week of the time horizon. The second iteration regards the second and third week of the time horizon. And so on. At each iteration, both strategies require that the decisions made on the first week (of the current planning horizon) must be saved and inserted into the overall problem solution. We refer to two kinds of decisions: production plan and distribution plan. The main differences between the two tested rescheduling strategies are in the second week (of the current planning horizon). According to PR, the production decisions made in the second week must be saved and constraint the production plan of the next iteration (see the red arrows in Figure 2), while they must be completely redefined according to CR. For clarity reasons, in Figure 3, we show an illustrative example, which represents the production and distribution decisions, returned by our model, with reference to the first two iterations, under PR and CR. As it can be seen, the first iteration is the same for both strategies. Then, the main difference is

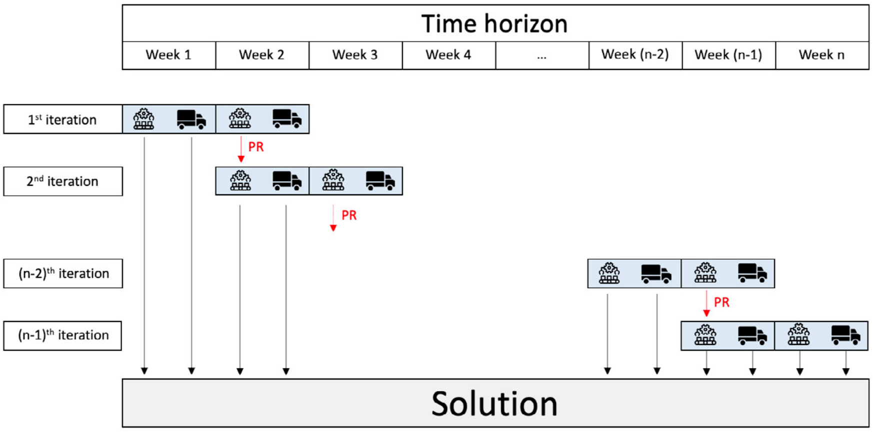

Fig. 2. Rolling horizon scheme

that the production decisions made in the second week of the first iteration are saved according to PR (i.e., red cells), while they are completely destroyed and redefined under the complete rescheduling approach.

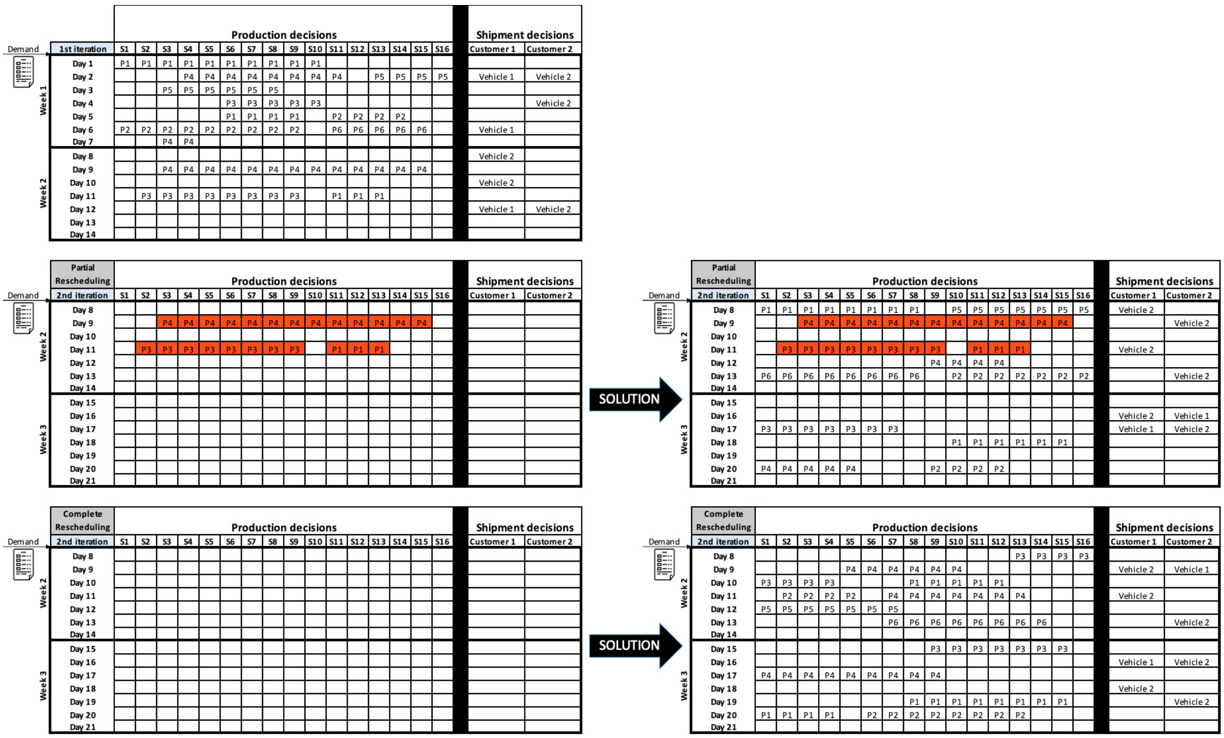

Fig. 3. Illustrative example: partial rescheduling and complete rescheduling

We have solved our optimization model on the 10 instances generated. Because of the computational complexity, the gap has been set to 3 %. The mean computational time was 15 seconds for PR and 37 seconds for CR. In Table 5, we show our results. As it can be noted, the complete rescheduling strategy can improve the current practices of the company. On average, savings greater than 4% can be achieved. In particular, the energy cost decreases because it is possible to better exploit mid-peak and off-peak hours. In addition, better inventory and delivery management is ensured. The production plan proposed by the model avoids the deterioration of raw materials that have a more stringent shelf-life, minimizing food waste. Given the limited computational time necessary for its solution, it can be a valid tool to support business decisions at an operational level. In fact, it can be effectively and efficiently solved once a week, taking into account the demand that arises from customers.

Table 5. Computational results

	Energy Cost [€]		Inventory Cost [€]		Shipping Cost [€]		Total Cost [€]		
	PR	CR	PR	CR	PR	CR	PR	CR	Δ (%)
I1	259.11	238.51	4043.94	3861.28	3730.00	3760.00	8033.05	7859.79	2.16
I2	275.65	229.94	4057.72	3750.78	3760.00	3760.00	8093.37	7740.72	4.36
I3	269.25	247.01	4119.27	3990.14	3770.00	3770.00	8158.52	8007.15	1.86
I4	268.12	244.88	4208.05	3833.49	3810.00	3680.00	8286.17	7758.37	6.37
I5	256.44	229.15	4182.10	3817.32	3810.00	3760.00	8248.54	7806.47	5.36
I6	274.31	236.17	4039.37	3888.81	3770.00	3810.00	8083.68	7934.98	1.84
I7	265.49	241.50	4089.34	3714.83	3810.00	3680.00	8164.83	7636.33	6.47
I8	263.41	239.79	3988.33	3775.37	3850.00	3730.00	8101.74	7745.16	4.40
I9	266.93	249.43	4055.23	3913.58	3720.00	3680.00	8042.16	7843.01	2.48
I10	266.74	236.57	4049.07	3745.18	3860.00	3720.00	8175.81	7701.75	5.80
Avg	266.55	239.30	4083.24	3829.08	3789.00	3735.00	8138.79	7803.37	4.12

5. Conclusions

In this paper, we have designed and tested an optimization model with the aim to support, in an integrated way, a company that deals with production, inventory and distribution of vegetable products. The model considers several real-life features such as the hourly fluctuations in energy price, changeover times on the production line, shelf-life of raw materials. Considering that customer demand occurs weekly and influences production and distribution plans, two rescheduling strategies have been implemented and compared, named respectively (i) partial and (ii) complete rescheduling. The first one reproduces the current behaviour of the company. The computational results show that the second strategy works better and can improve the operational practices of the firm.

Future developments include the design of a conceptual framework with the aim to integrate the proposed model into an advanced automated planning system, in accordance with the Industry 4.0 paradigm. Among the enabling technologies of the fourth industrial revolution, the model significantly exploits the value of Big Data, to support and make decision-making more flexible in the context of smart manufacturing. The adoption of smart practices is particularly interesting in the food industry context as they can minimize the amount of wasted food, reduce energy consumption, protecting environmental sustainability.

Our future research will be also focused on the possibility of using heuristic approaches to solve larger intances. Moreover, the model will be enhanced considering a multi-line version.

References

[1] Kumar, Ramesh, L. Ganapathy, Ravindra Gokhale, and Manoj Kumar Tiwari. (2020) “Quantitative approaches for the integration of production and distribution planning in the supply chain: a systematic literature review.” *International Journal of Production Research* **58** (11): 3527–3553.

[2] Fahimnia, Behnam, Reza Zanjirani Farahani, Romeo Marian, and Lee Luong. (2013) “A review and critique on integrated production–distribution planning models and techniques.” *Journal of Manufacturing Systems* **32** (1): 1–19.

[3] Guido, Rosita, Giovanni Mirabelli, Enrico Palermo, and Vittorio Solina. (2020) “A framework for food traceability: case study – Italian extra-virgin olive oil supply chain .” *International Journal of Industrial Engineering and Management* **11** (1): 50–60.

[4] Mirabelli, Giovanni, and Vittorio Solina. (2020) “Blockchain and agricultural supply chains traceability: research trends and future challenges.” *Procedia Manufacturing* **42**: 414–421.

[5] Amorim, P., H. Meyr, C. Almeder, and B. Almada-Lobo. (2013) “Managing perishability in production-distribution planning: a discussion and review.” *Flexible Services and Manufacturing Journal* **25**: 389–413.

[6] Gahm, Christian, Florian Denz, Martin Dirr, and Axel Tuma. (2016) "Energy-efficient scheduling in manufacturing companies: A review and research framework." *European Journal of Operational Research* **248** (3): 744–757.

[7] Ouelhadj, Djamila, and Sanja Petrovic. (2009) "A survey of dynamic scheduling in manufacturing systems." *Journal of Scheduling* **12** (4): 417–431.

[8] Gong, Guiliang, Raymond Chiong, Qianwang Deng, Wenwu Han, Like Zhang, Wenhui Lin, and Kexin Li. (2020) "Energy-efficient flexible flow shop scheduling with worker flexibility." *Expert Sytstems with Applications* **141**.

[9] Shrouf, Fadi, Joaquin Ordieres-Meré, Alvaro García-Sánchez, and Miguel Ortega-Mier. (2014) "Optimizing the production scheduling of a single machine to minimize total energy consumption costs." *Journal of Cleaner Production* **67**: 197–207.

[10] Aghelinejad, Mohammad Mohsen, Yassine Ouazene, and Alice Yalaoui. (2016) "Machine and Production Scheduling Under Electricity Time Varying Prices." In *Proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management 2016*: 992–996.

[11] Angizeh, Farhad, Hector Moreno, Abhinay Vedpathak, and Masood Parvania. (2020) "Optimal production scheduling for smart manufacturers with application to food production planning." *Computers and Electrical Engineering* **84**.

[12] Ramos, António G., and José Leal. (2017) "ILP model for energy-efficient production scheduling of flake ice units in food retail stores." *Journal of Cleaner Production* **156**: 953–961.

[13] Wang, Shijin, Ming Liu, Feng Chu, and Chengbin Chu. (2016) "Bi-objective optimization of a single machine batch scheduling problem with energy cost consideration." *Journal of Cleaner Production* **137**: 1205–1215.

[14] Cheng, Junheng, Feng Chu, Ming Liu, Peng Wu, Weili Xia. (2016) "Bi-criteria single-machine batch scheduling with machine on/off switching under time-of-use tariffs." *Computers and Industrial Engineering* **112**: 721–734.

[15] Cui, Weiwei, Huali Sun, and Beixin Xia. (2019) "Integrating production scheduling, maintenance planning and energy controlling for the sustainable manufacturing systems under TOU tariff." *Journal of the Operational Research Society*.

[16] Biel, Konstantin, and Cristoph H. Glock. (2016) "Systematic literature review of decision support models for energy-efficient production planning." *Computers and Industrial Engineering* **101**: 243–259.

[17] Chandra, Pankaj, and Marshall L. Fisher. (1994) "Coordination of production and distribution planning." *European Journal of Operational Research* **72**: 503–512.

[18] Bilgen, Bilge, and Yelda Çelebi. (2013) "Integrated production scheduling and distribution planning in dairy supply chain by hybrid modelling." *Annals of Operations Research* **211** (1): 55–82.

[19] Chen, Huey-Kuo, Che-Fu Hsueh, and Mei-Shiang Chang. (2009) "Production scheduling and vehicle routing with time windows for perishable food products." *Computers and Operations Research* **36** (7): 2311–2319.

[20] Kopanos, Georgios M., Luis Puigjaner, and Michael C.Georgiadis. (2012) "Simultaneous production and logistics operations planning in semicontinuous food industries." *Omega* **40** (5): 634–650.

[21] Devapriya, Priyantha, William Ferrell, and Neil Geismar. (2017) "Integrated production and distribution scheduling with a perishable product." *European Journal of Operational Research* **259** (3): 906–916.

[22] Geismar, H. Neil, Gilbert Laporte, Lei Lei, and Chelliah Sriskandarajah. (2008) "The Integrated Production and Transportation Scheduling Problem for a Product with a Short Lifespan." *INFORMS Journal on Computing* **20** (1): 21–33.

[23] Belo-Filho, M.A.F., P. Amorim, and B. Almada-Lobo. (2015) "An adaptive large neighbourhood search for the operational integrated production and distribution problem of perishable products." *International Journal of Production Research* **53** (20): 6040–6058.

[24] Gestore dei mercati energetici (GME), website: https://www.mercatoelettrico.org/It/Default.aspx.