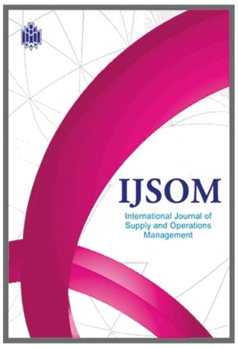
International Journal of Supply and Operations Management

IJSOM

2023, Volume 10, Issue 3, pp. 396-416
ISSN-Print: 2383-1359
ISSN-Online: 2383-2525
www.ijsom.com



A Lot Sizing and Scheduling Approach on Non-Identical Parallel Machines for Cement Grinding Process Considering Process-Specific Characteristics

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Abstract

Integrating the lot sizing and scheduling problems for improving capacity utilization in process industries is crucial. In order to deal with this problem realistically and to obtain applicable schedules, it is a prerequisite to consider the typical characteristics of the industry under consideration. From this point of view, in this study, the lot sizing and scheduling problem in cement grinding, a multi-product, multi-period optimization problem with non-identical parallel machines, is addressed by considering the unique and industry-specific characteristics of the process. Besides applicability, it is aimed to create schedules that minimize total costs, including inventory holding, production, electricity, and lost sales. A lot sizing and scheduling model (LSM) based on the General Lot Sizing Problem (GLSP) and a capacity control model (CCM) derived from LSM has been developed for the considered problem with these objectives. The proposed approach based on the cyclical running of LSM and CCM has been applied for one year using the real data of a firm operating in the cement industry. The performance of this approach has been evaluated by comparing it with the firm's realized performance during that year. As a result, the proposed approach has significantly reduced inventory holding costs by 47.51%, production during setups by 62.54%, production after setups by 1.49%, and electrical energy by 8.65%.

Keywords: Cement grinding process, Linear programming, Lot sizing, Scheduling, Energy efficiency, General Lot Sizing Problem.

1. Introduction

The cement industry, categorized under process industries, is one of the most pollutant industries (Van Oss and Padovani, 2003; Ekinci et al., 2020). It stands out with high electrical energy usage and time-dependent electricity pricing. Cement production is a hybrid structured process with consecutive stages, starting from continuous processes and turning into a discrete type. In this production process, the planning of continuous processes is carried out long-term. Inventory tracking of the products is controlled by monitoring the quantities in the silos where the products are stored. In many process industries, including cement production, demand is in a floating structure, and even full capacity utilization may not meet the demand in some periods. Therefore, holding inventory is considered economically advantageous for this process than having a capacity surplus (Clark et al., 2011). Short-term production scheduling, the layer between these two processes, is mainly conducted to fill the cement silos to the maximum level and satisfy the forecasted product demands from the inventory. This approach might lead to production in periods with high electricity prices, surplus production, high holding costs, extra changeovers between product types, and high cost.

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DOI: 10.22034/IJSOM.2023.109501.2449
*This study has been prepared based on the doctoral thesis of the corresponding author titled "Scheduling model for hybrid production type in process industries."

The cement production process involves raw material preparation, raw meal grinding, clinker production, cement grinding, and packing sub-stages requiring a high electrical energy level. Among these sub-processes, cement grinding, where the production type is turned into the discrete structure, uses the largest proportion of the total electrical energy consumed during the cement production process, with a rate of about %30-%40 (Jankovic et al. 2004; Mejeoumov, 2007; Madlool et al., 2011; Schneider et al., 2011; Swanepoel et al., 2014; ICR Research, 2015). Cement grinding is also the bottleneck process that determines the speed of the whole cement production process. Accordingly, improvements in this process would increase performance and energy usage efficiency throughout the cement production process, reducing CO_2 emissions (Atmaca et al., 2012). One of the most significant improvements in the cement grinding process is to optimally schedule the process in the short term by considering industry-specific characteristics to minimize the total costs incurred during the process.

Production scheduling is a critical process required to be carried out efficiently to meet the customers' needs and wishes at the desired cost level. In the process industries, production scheduling problem has gained more attention in recent years (e.g., Georgiadis et al., 2019; Castro and Mostafaei, 2019; de Prada et al., 2019; de Matta, 2018; Trattner et al., 2018; Polon et al., 2018; Gajic et al., 2017; Baldea et al. 2015; Camargo et al. 2012; Figueira et al., 2013; Haksöz and Pinedo, 2011; Transchel et al. 2011) with the effect of the changes in demand structure and increase in product variety.

A large number of studies have addressed the production scheduling problem by developing mathematical models in the literature. Although some of these models seem to be successful theoretically, they have been criticized for their applicability (Akkerman and van Donk, 2009; Crawford et al., 1999). Unrealistic assumptions that make the modeling easier and shorten the solution time constitute one of the most important reasons for the failures in the real-life applications of these models (Mendez et al., 2006). Addressing the production scheduling problems under realistic assumptions with industry and process-specific characteristics increases the applicability of the models.

The make-to-stock production strategy is followed in the cement industry, like most process industries. The primary focus is on capacity utilization in long- and short-term production planning due to the high cost and special-purpose equipment and machines used (Ashayeri et al., 1995; Jovan, 2002, Napoleone et al., 2021). The cement production process has many characteristics, such as having a hybrid production structure, having a bottleneck sub-process in the entire production process, multi-product types, sequence-dependent setup times, and costs. These characteristics require integrating the scheduling and lot-sizing problems (Kallrath, 2002) because the available production capacity is determined by the size and sequence of the lots (Meyr, 2000). Therefore, the integration of lot sizing and scheduling problems is crucial for obtaining feasible, applicable, and cost-effective schedules (Almada-Lobo et al., 2015).

This study addresses the short-term scheduling of the cement grinding process integrated with lot sizing, considering industry-specific characteristics such as time-varying electricity pricing, alternative recipes, sequence-dependent setup times, varying production times, and fluctuating demand structure to create practically applicable minimum cost schedules. A linear programming model, LSM, has been proposed based on the GLSP to minimize total costs, including inventory holding, production, electricity, and lost sale costs. Also, by modifying LSM, another model, called CMM, has been developed. These two models have been integrated by applying a cyclical approach to managing capacity and adjusting products' inventory levels. Finally, the proposed approach has been applied to the problem of a cement manufacturing company operating in Turkey.

Previous studies have been reviewed addressing the scheduling and lot-sizing problems in the cement industry. The methodologies they followed and the characteristics they took into account have been analyzed to determine where this study might contribute to the literature. This study aims to contribute to the literature on the following points:

- In this study, the scheduling problem has been addressed integrated with lot sizing in the cement grinding process considering various process and industry-specific characteristics, and a GLSP-based mathematical model has been proposed. The considered characteristics include sequence-dependent setup times and costs, setup carry-over, time-varying electricity prices, varying production times, alternative recipes, minimum batch size constraints, and lost sales. Also, capacity and inventory management processes have been incorporated into the lot sizing and scheduling process. To the best of the authors' knowledge, there have been no prior studies considering all these features simultaneously in the context of the cement industry.
- This study modeled the problem based on the GLSP with a classical time representation scheme modification. As the modification, sub-periods with different electricity prices have been incorporated under the micro periods of the classical GLSP time representation scheme to consider the time-varying electricity prices feature of the cement industry in preparing schedules.

The following section presents a literature review conducted in parallel with the scope of this study. The previous research that has addressed scheduling and lot-sizing problems in the cement and process industries has applied to real case studies included in the review. Cement production and its scheduling process have been introduced in Section 3. Afterward, in Section 4, details of the problem and the developed model have been provided. In Section 5, details of the proposed cyclical approach and the developed algorithm have been presented. Section 6 provides the experimental results that demonstrate the model performance. The sensitivity analysis conducted to reveal some parameters' effect on the total cost has been placed in Section 7, and the study has been finalized with the conclusion section.

2. Literature Review

Prior studies have addressed the scheduling problem in the cement industry. Castro et al. (2009) handled the short-term scheduling problem of continuous multi-product plants, including cement facilities, by considering time-dependent electricity pricing and availability and multiple intermediate due dates. They presented a continuous-time formulation based on the resource-task network framework to obtain minimum electricity cost schedules. The main parameters of their models were hourly changed electricity cost, the capacity of storage units, demands of products, power requirements of products in machines, maximum power consumption for hours of days, maximum processing rates of machines, and processing rates of products in machines. They solved small-size problems effectively with their formulation and prepared schedules over one week. Castro et al. (2011) studied the same problem as Castro et al. (2009) by again considering variable electricity pricing and availability differently in the time formulation. They used a non-uniform discrete-time grid in which the duration of time intervals can be different. Rehman and Asad (2010) addressed the short-term production scheduling of the cement quarry operations, and Asad (2011) the long-term scheduling problem of cement quarry operations. Vujanic et al. (2012) developed a MILP model to schedule individually two machines used in the rock crushing process of a cement plant by considering hour-based deterministic electricity pricing. Mitra et al. (2012) handled a production planning problem for continuous power-intensive processes considering time-dependent electricity pricing. They formulated a discrete-time Mixed-Integer Linear Programming (MILP) model and tested their approach using Castro et al. (2011) 's test instances of Ex5-Ex10 for cement plants and compared their model's performance using different operating modes. They obtained the same or lower optimality gap for all instances than Castro et al. (2011). Alves et al. (2016) studied lot sizing and scheduling problem in the refractory material production process by using the data derived based on the real data of a refractory cement manufacturer. They handled the problem as a single machine problem and considered the sequence-dependent setup times. They proposed a Mixed-Binary-Integer Linear Programming Model for this problem by using a discretized time horizon to minimize total inventory and back-ordering costs. Gajic et al. (2017) dealt with the production scheduling problem in a different process industry from the cement industry by considering the variable electricity cost. They addressed the production scheduling problem considering variable electricity prices in the melting process, the initial process of stainless steel production. They proposed a MILP model to minimize the related cost of electricity and production delays. They implemented their system in a melt shop and tested its validity. As a result, they obtained a 3% reduction in electricity cost with their approach. Vu et al. (2021) addressed quarry production scheduling problem considering geological uncertainties with the stochastic MILP model. Gerami et al. (2021) developed a scheduling model for energy consumption of a micro grid of several industrial factories, including a cement factory.

The cement industry has many typical features of process industries and its process-specific characteristics. In the prior researches that have addressed lot sizing and scheduling problem in the process industries, CLSP (Capacitated Lot Sizing Problem) and GLSP are among the most widely used problem types (Almada-Lobo et al., 2015), and parameters related to the demand, capacity, setup, and inventory are frequently used primary parameters. Besides, backlogging (Jans and Degraeve, 2004; Stadtler and Sahling, 2013; Martinez et al., 2018); lost sales (Transchel et al., 2011); lead time (Stadtler and Sahling, 2013); overtime (Koçlar, 2005; Seeanner and Meyr, 2013), perishability (Wei et al., 2019); external purchasing, standby time and cost (Seeanner and Meyr, 2013); profit margins of products (Transchel et al., 2011) are also considered.

In one of the studies handling the lot sizing and scheduling problem simultaneously with an application on real case studies, Marinelli et al. (2007) developed a hybrid Continuous Setup Lot Sizing problem (CSLP) - CLSP model using the data of a packaging company producing yogurt. They assumed that setup times and costs are sequence-independent and considered the seasonality and trend of the data in their model. Almada-Lobo et al. (2007) studied a single-stage single machine multi-item CLSP with sequence-dependent setup times and costs by considering setup carry-overs in the glass container industry. Hans and van de Velde (2011) addressed a single-level multi-item big bucket capacitated lot-sizing problem for sand castling operations with setup carry-overs. Stadtler and Sahling (2013) handled a multi-stage Proportional Lot Sizing and Scheduling Problem (PLSP) and developed a model to apply to the pharmaceutical industry. Meyr (2000) addressed the simultaneous lot sizing and scheduling problem of multiple products on a single production line considering sequence-dependent setup times and costs. He extended the GLSP formulation of Fleischmann and Meyr (1997), incorporating sequence-dependent setup times to minimize the total cost of inventory holding and setup. Meyr (2002) extended the GLSP formulation of Meyr (2000) for non-identical parallel production lines.

Koçlar (2005) dealt with the single-level, multi-product GLSP with sequence-dependent setup times and costs and developed a mathematical model based on the models of Fleischmann and Meyr (1997) and Meyr (2000). She modified these models' minimum batch size constraints and made the minimum batch sizes splittable between the periods. Also, she considered the production costs and overtime usage option in her model. Koçlar and Süral (2005) modified the minimum batch size constraint of Fleischmann and Meyr (1997)'s GLSP formulation.

Transchel et al. (2011) dealt with a two-stage short to mid-term real production planning and scheduling problem of a chemical company. They modeled the problem based on the GLSP by incorporating problem-specific characteristics into the model. Their model considered minimum batch sizes of products, sequence-dependent setup times, setup costs, and setup carry-overs and used the lengths of macro-periods as months. Seeanner and Meyr (2013) addressed the lot sizing and scheduling problem in a multi-stage environment, including heterogeneous parallel production lines. They modeled the problem based on the GLSP with a common time structure for each line. Their model considered sequence-dependent setup cost and times, minimum lot sizes, setup carry-overs, external purchasing, overtime, and standby conditions. Their model did not allow backlogging and lost sales. Stefansdottir et al. (2017) incorporated a classification structure that distinguishes setup and cleaning operations which are important in process industries, into their lot sizing and scheduling model. They developed a MILP model and applied it to a real-life problem of a dairy production company. Martinez et al. (2018) addressed lot-sizing and scheduling problems integrated with process configuration decisions in the pulp industry. They formulated the problem based on the classical GLSP. Georgiadis et al. (2019) addressed a lot-sizing and scheduling problem in the yoghurt industry with a real-life industry case. They proposed a MILP model and evaluated their model's performance by comparing the analyzed company's realized schedule. As a result, they obtained around a 20% decrease in the total cost, including cost items such as production, setup, lost sales, and missed safety stock penalty. Carvalho and Nascimento (2022) analyzed the lot sizing and scheduling problem with non-identical parallel machines. Their study considered limited capacity, setup carry-over, sequence-dependent setup times, and costs. They developed a MIP model based on the facility location problem, and to solve the problem, they proposed three approaches based on the hybridization of the relax-and-fix and fix-and-optimize methods with the path-relinking and kernel search heuristics. Finally, they compared and evaluated their proposed approaches' performance using some test instances in the literature. Mediouni et al. (2022) addressed a multi-period multi-level capacitated lot sizing and scheduling problem in a dairy production process and modeled the problem with a MIP formulation. They designed ten experiments to reflect the real-life problem of the case company based on various criteria, including production demand, storage cost, back-order cost, and capacity restrictions. Finally, they applied an exact method and a relax- and-fix algorithm depending on the experiment's problem size. Kubur Özbel and Baykasoğlu (2023) addressed GLSP by considering sequence-dependent setups and back-orders and developed a MIP model for the problem. Furthermore, they proposed a solution approach that integrates the Simulated Annealing algorithm with the MIP model they developed.

Tang and Wang (2022a) developed a multi-objective lot sizing and scheduling model, which includes the objectives of minimization of maximum completion time and total product switching cost for the process industry under a mass customization production environment. They considered product demand as a fuzzy variable. They proposed an improved multi-objective genetic particle swarm algorithm to simulate and solve the model they developed. In another study by Tang and Wang (2022b), a multi-objective lot sizing and scheduling model in the process industry was developed by considering uncertainties regarding production ability and market demand. They incorporated the predictive control process of the model for obtaining optimal decisions on the total completion time and production cost decisions. Their data set was obtained as a result of the simulation analysis based on the data of a chemical company. In the predictive control stage of their approach, they applied an algorithm containing Elman neural network, the developed optimization model, and the developed multi-objective particle swarm optimization algorithm.

3. Cement Production Process and Its Scheduling

Cement production involves many sequential processes, from quarrying to packaging and storage of ground cement. The cement production flow chart showing the processes, inputs, and outputs and the main stages of cement production is given in Figure 1.

In stage 1, raw materials of cement (for example, limestone and clay) are extracted from the quarry, crushed, stocked, premixed, and reduced in size. Then the prepared materials are brought into fine dust (raw meal). The obtained raw meal is homogenized and stored in the raw meal silos. After the raw meal grinding process, the raw meal is processed into clinker by a series of operations in the second stage. In the last stage, the additives (such as limestone, pozzolana, and fly ash) required by the cement type are added to the clinker in the necessary proportions and ground together in cement mills. In cement mills, these additives and clinker are stored in bunkers. Due to the constraint that cement mills may not have the bunkers of all additives, all cement types may not be ground in all cement mills. Also, cement types can be ground using different recipes in different cement mills. Besides this, cement mills' processing capacities may also vary. Fine dusted cement is stocked in silos, which can have different capacities and contain only one type of cement. In the last sub-process of cement production, cement is packaged (Atmaca and Yumrutaş, 2014; Gao et al., 2016). The cost of electricity, one of the most significant cost items in cement production, differs in three periods during a day.

The cement manufacturing process is flow-type until the cement grinding stage. At this stage, it becomes discrete. Planning and scheduling the flow-type processes are not so challenging as discrete-type. However, the cement grinding process, which determines the cement production process's speed and uses most of the electricity consumed in the process, requires a systematic scheduling approach that considers the specific characteristics of the process.

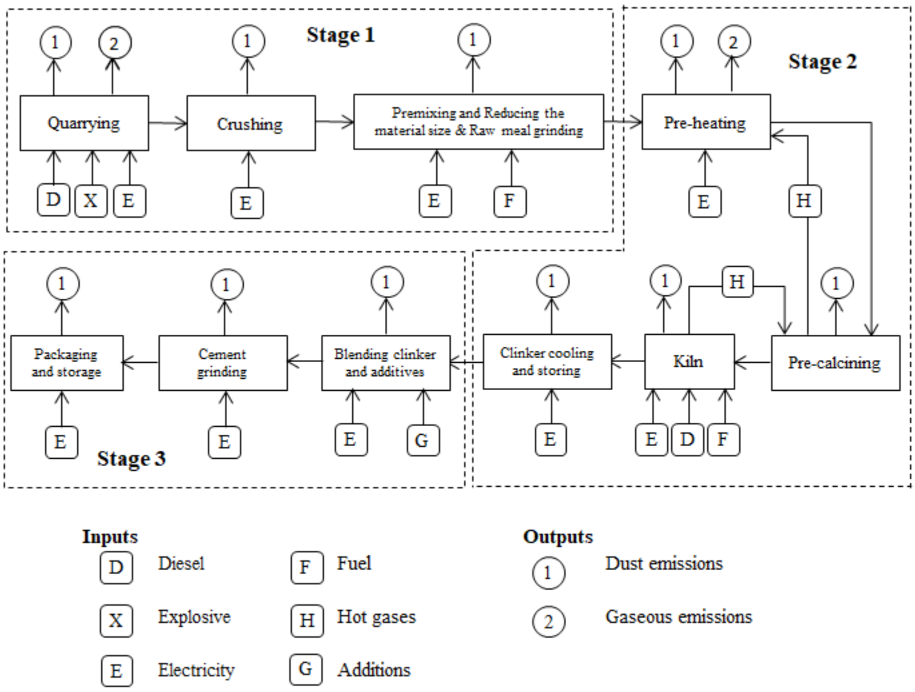

Figure 1. Process flow diagram of cement production (Adapted from Gutiérrez et al., 2017)

Different cement types are ground in mills with various capacities and processing properties in the cement grinding process. Many process characteristics affect scheduling in the cement grinding process. The cement types can be produced with alternative recipes. The grinding time can be different in each run due to the quality variations of the clinker and additives used, electricity pricing varies in three time periods during a day, and some cement types can have minimum batch size constraints. The setup times and costs are sequence-dependent. For example, suppose the second of the two types of cement to be ground consecutively in the same mill does not contain any additives included in the previously ground cement type in the transition from the first ground cement type to the second. In that case, the mill must be processed until the additives in the first cement disappear completely. The ground cement types are stored in silos that can only hold one type of cement. In this process, lot sizing and scheduling include deciding which product type to produce in which mill, with which lot size, and using which recipe, sequence, and sub-period become notably complicated.

Fluctuating demand structure is also an important characteristic of the cement industry. In some periods, the demand for products may exceed the production capacity. Therefore, the make-to-stock production strategy is adopted, and production is made to fill production silos to the maximum level to cope with this situation. However, this approach may cause surplus inventory during periods with low demand, unnecessary use of the mills during high electricity pricing periods, overproduction, high numbers of setups, and hence increases in the total costs arising in the process. Therefore, to meet the product demands with minimum cost, it is necessary to anticipate the capacity deficiencies that may arise from demand variations and prepare the production system accordingly.

This study addresses the lot sizing and scheduling problem in the cement grinding process, considering process-specific characteristics to create feasible, applicable, and minimum cost schedules. To achieve this aim, in addition to lot sizing and scheduling, product demand and production capacity need to be managed efficiently, and inventory levels should be increased when high demand volumes are anticipated, rather than keeping high inventories continuously.

4. Problem Definition and Details of the Model

4.1. Problem Definition and Model Assumptions

This study addresses the lot sizing and scheduling problem in the cement grinding process with a real case study of a cement manufacturing company operating in Turkey. The firm operates under an aggregate corporation of seven companies in four different sectors. This corporation employs more than 1,000 employees. The production system under consideration can be considered a flexible flow shop, characterized by the presence of parallel machines at some stages, the ability to process products on alternative machines, and the different processing times of the machines (Wu et al., 2018). In Figure 2, the cement grinding process that the real-life problem addressed has been depicted.

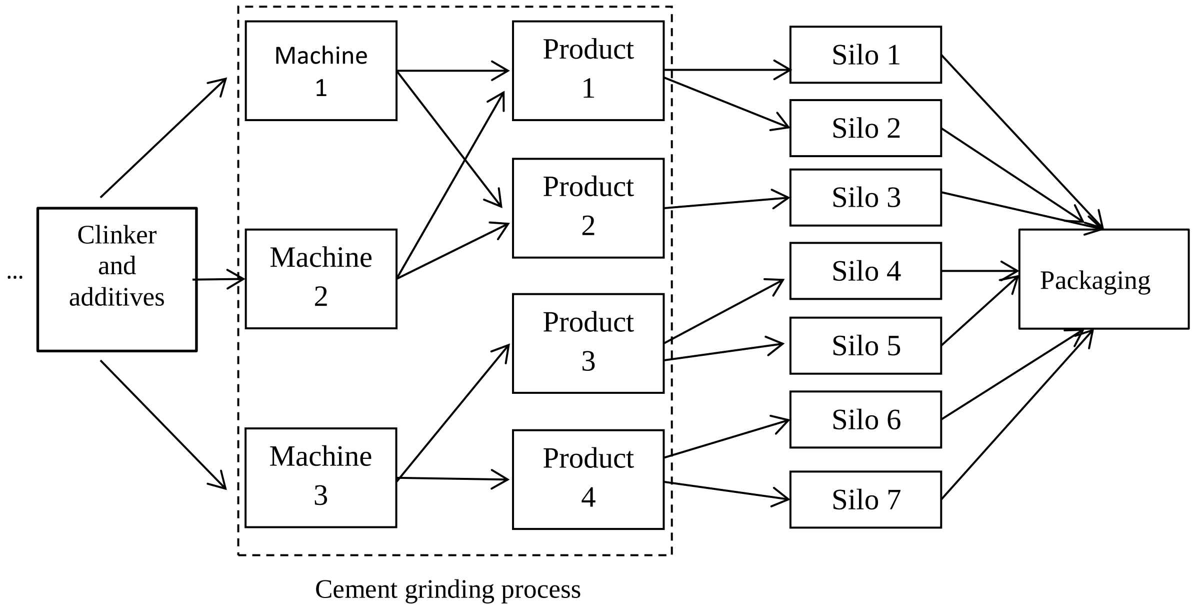

Figure 2. Schematic diagram of the addressed problem

The addressed cement grinding process is characterized as a single-stage, multi-product process with non-identical parallel machines. Hence, the problem is a capacitated, single-stage, multi-product lot sizing and scheduling problem with non-identical parallel machines. A linear programming model is proposed to address this problem by considering many industry-and-company-specific characteristics, including time-varying electricity pricing, alternative recipes, grinding time variability, sequence-dependent setup times and costs, and minimum lot size constraints.

This company grinds four types of cement in three cement mills that differ in production capacities, cement types they can grind, and setup times. In the remaining of the study, cement types are expressed as products and cement mills as machines. Products and machines are denoted by $j \in N := \{1, \dots, N\}$ and $m \in M := \{1, \dots, M\}$, respectively. Two products ($j = 1$ and $j = 2$) can be ground in two machines ($m = 1$ and $m = 2$) with different recipes, and two products ($j = 3$ and $j = 4$) are ground with a single recipe in a single machine ($m = 3$).

Machines use electrical energy during the grinding of the products. ec_{mj} denotes the electrical energy consumed while producing product j by machine m in kWh/ton differs for machine-product pairs. The electricity price varies in three different periods during the day. The most expensive period (peak) is between 5:00 pm- 10:00 pm, the cheapest is 10:00 pm - 6:00 am, and the average is 6:00 am-5:00 pm. While modeling the problem, it is necessary to determine the amount of production during and after setup in these periods where the price of electrical energy varies. In this study, the problem is modeled based on GLSP. GLSP is a hybrid model that combines big and small bucket problems. In GLSP, the lot sizing and scheduling problem is addressed simultaneously with capacity constraints, continuous lot sizes, and dynamic and deterministic demands (Fleischman and Meyr, 1997).

The classical GLSP time representation structure includes macro and micro-periods (positions) (Drexl and Kimms, 1997; Fleischman and Meyr, 1997). In this study, the periods in which electricity pricing changes are integrated into this structure as "sub-periods." Macro-periods, sub-periods, and micro-periods are denoted by $t \in T := \{1, \dots, T\}$, $z \in Z := \{1, \dots, Z\}$, and $n \in K := \{1, \dots, K\}$, respectively.

In GLSP, the product demands are given for macro-periods and met at the end of the macro-periods. The length of the macro-periods for the lot sizing and scheduling problem addressed in this study is determined by considering the company's past sales and order fulfillment time. The past sales have indicated that daily sale quantities of products are very close to the sum of the company's daily production capacity and the inventories held on many days, even on some days more than this amount. Due to the industry structure, most orders are taken to fulfill on the same day. Therefore, it is decided to use macro-periods as days to make the model respond to these daily variations. It is assumed that macro-periods are equidistant. As a result of the length of macro-periods, there are three sub-periods with specific durations within each macro- period for each machine. The length of sub-period z in minutes is denoted by Cap_z and is 660, 300, and 480 for the average, peak, and cheapest sub-periods, respectively.

Each sub-period contains a fixed number of micro-periods that do not overlap. The indexes of the first and the last micro-period in sub-period z of macro-period t are denoted by F_{tz} and L_{tz}, respectively. In the model, the length of a micro-period is expressed as the amount produced in that micro-period. The model decides the lengths of micro periods. In Figure 3, the used time framework is presented. This framework is applied to all machines.

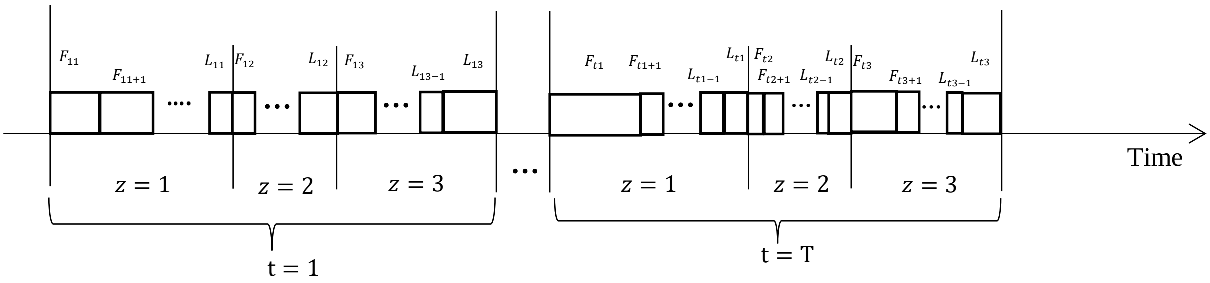

Figure 3. The used framework for macro-periods, sub-periods, and micro-periods in the GLSP

Similar to Transchel et al. (2011), the number of micro periods for each machine is determined as the number of products that can be produced on that machine. Only one type of product can be produced in each micro-period, and a single changeover can be performed. Thus, there are three sub-periods of specific lengths for each machine in each macro-period and two micro-periods in each sub-period.

Due to the quality variabilities of the additives and clinker used in the products, the amount of products that the machines can produce per hour varies. For example, $m = 1$ may produce 45 to 50 tons of $j = 1$ per hour, ranging from 35 to 40 tons of $j = 2$ per hour. Hourly production quantities of products in machines for each micro-period are derived with normal distribution within the upper and lower production quantity limits of machine-product pairs to reflect this variability. These derived values are used in the model by converting them into the production time in units of ton/minute and denoted by $\mathrm{P_{mjn}}$.

The setup times and costs are sequence-dependent. Setup time for the transition from product j to product i in machine m, denoted by $\mathrm{ST_{mij}}$, and setup cost for the transition from product j to product i is denoted by $\mathrm{cst_{mj}}$. $\mathrm{cst_{mj}}$ refers to the unit cost of production until the additives of product j disappear in the transition to product i. The transition from product 2 to 1 in the first and second machines takes 45 minutes; the transition from product 4 to product 3 in the third machine takes 30 minutes.

The ground products are stored in silos with different storage capacities, and a silo can hold only one type of product. The company has seven silos, ranging from 2,500 to 10,000 tons. Changing the type of product stored in a silo requires a long time and a costly cleaning process. The upper limit of inventory of product j (ton), denoted by $\mathrm{maxI_j}$ equals the total capacity of the silos that the product j is allowed to be assigned. $j = 1$ and $j = 2$ are needed to be produced with different minimum lot sizes on the first and second machines. The minimum lot size of product j in machine m in tons is expressed by $\mathrm{minim_{mj}}$.

In macro-period t, if total production and inventory on hand are insufficient to meet the demand of product j, the sale of the amount that cannot be met is lost. This lost sale quantity of product j in macro-period t is represented by $\mathrm{rls_{jt}}$ in the model.

The linear programming model has been developed for this problem to determine which product should be produced in which machine in which lot size, sub-period, and sequence to minimize total production, setup, consumed electrical energy, inventory holding, and lost sales costs.

Several model assumptions specific to the problem are mentioned while introducing the problem. Other assumptions of the model, which are among the basic assumptions of Koçlar's (2005) GLSP model, are as follows:

- Product demands are dynamic and deterministic.
- Product lot sizes are continuous. The production of a product may take place in multiple consecutive periods. The lot size, in this case, is equal to the total amount of products produced in these successive periods.
- Minimum lot sizes may be divided into two consecutive positions except the first and last positions of the planning period, in case of capacity restrictions.
- Machines' setup state is preserved over idle periods.
- A setup operation has to be started and finished within the same period. It cannot be divided into periods.
- The zero-switch property does not hold. Production of a product may occur in a period even if its incoming inventory is not zero.

4.2. Model Formulation

In this study, a lot sizing and scheduling model, LSM, is developed mainly based on the model of Koçlar (2005). The formulation of Koçlar (2005) for a single machine has been generalized to parallel machines, and the time representation structure used by Koçlar (2005) has been modified by integrating sub-periods between macro and micro-periods. In addition, the constraints and decision variables related to the industry and problem-specific characteristics presented in the problem definition section have been added to the model. The indices, parameters, and decision variables of the model are as follows:

Sets and Indices:

N: Set of products: $i, j \in N$ ($i/j = 0$ denotes the initial setup state)
T: Set of macro-periods: $t \in T$
Z: Set of sub-periods: $z \in Z$
K: Set of micro-periods/positions: $n \in K$
M: Set of machines: $m \in M$

Parameters:

h_j: Unit holding cost of product j per day (TL/ton)
I_{j0}: Initial inventory of product j (ton)
$maxI_j$: Upper limit of inventory of product j (ton)
$minim_{mj}$: Minimum batch size of product j in machine m (ton)
d_{jt}: Demand for product j in period t (ton)
Cap_z: Length of sub-period z (minute)
$encost_z$: Electrical energy price in sub-period z (TL/kWh)
ec_{mj}: Electrical energy consumed while producing product j in machine m (kWh/ton)
F_{tz}: Index for the first position in sub-period z of macro-period t
L_{tz}: Index for the last position in sub-period z of macro-period t ($z = Z$ denotes the last sub-period of the last macro-period t)
l_{mj}: 1, if product j is compatible with machine m; 0, otherwise
cst_{mj}: Setup cost for the transition from product j to product i in machine m (TL/ton)
ST_{mij}: Setup time for the transition from product j to product i in machine m (minute)
P_{mjn}: Unit production time of product j in position n in machine m (minute/ton)
CP_{mj}: Unit production cost of product j in machine m (TL/ton)
M: Big number
lsc_j: Lost sale cost of product j (TL/ton)
$infin_j$: Safety stock of product j (ton)

Decision Variables:

X_{mjn}: Units of product j produced in position n in machine m (ton)
W_{mjn}: Setup variable which takes 1, if product j is assigned to position n in machine m; 0, otherwise
Y_{mjn}: Auxiliary binary variable to determine whether product j is produced in position n in machine m
I_{jt}: Inventory of product j at the end of macro-period t (ton)
δ_{mijn}: 1, if there is a changeover from the product i in position $n-1$ to product j in position n in machine m; 0, otherwise.
$Tencost_t$: Total cost of electrical energy consumed in macro-period t (TL)
TX_{jt}: Total units of product j produced in macro-period t after setup operation (ton)
QST_{jt}: Total units of product j produced in macro-period t during the setup time (ton)
PT_{mtz}: Production time in sub-period z of macro-period t for machine m (minute)
TS_{mtz}: Setup time in sub-period z of macro-period t for machine m (minute)
rls_{jt}: Units of lost sale of product j in macro-period t (ton)

Min Z= $\sum_{j=1}^{N}\sum_{t=1}^{T} h_j I_{jt} + \sum_{m=1}^{M}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{n=1}^{K}((ST_{mij}\,\delta_{mijn})/P_{min})cst_{mi} + \sum_{m=1}^{M}\sum_{j=1}^{N}\sum_{n=1}^{K} CP_{mj} X_{mjn} + \sum_{t=1}^{T} Tencost_t + \sum_{j=1}^{N}\sum_{t=1}^{T} rls_{jt}\, lsc_j$ (1)

Subject to

$\sum_{m=1}^{M}\sum_{z=1}^{Z}\sum_{i=1}^{N}\sum_{n=F_{tz}}^{L_{tz}}\left[\left(ST_{mji}\delta_{mjin}\right)/P_{mjn}\right] = QST_{jt}$ $\forall t, j > 0$ (2)

$\sum_{m=1}^{M}\sum_{z=1}^{Z}\sum_{n=F_{tz}}^{L_{tz}} X_{mjn} = TX_{jt}$ $\forall t, j$ (3)

$I_{jt} = I_{j(t-1)} + TX_{jt} + QST_{jt} + rls_{jt} - d_{jt}$ $\forall t, j$ (4)

$I_{jt} \le maxI_j$ $\forall t, j$ (5)

$\sum_{j=1}^{N}\sum_{i=1}^{N}\sum_{n=F_{tz}}^{L_{tz}} ST_{mji}\,\delta_{mjin} = TS_{mtz}$ $\forall m, t, z$ (6)

$\sum_{j=1}^{N}\sum_{n=F_{tz}}^{L_{tz}} P_{mjn} X_{mjn} = PT_{m,t,z}$ $\forall m, t, z$ (7)

$$TS_{mtz} + PT_{mtz} \leq Cap_z \qquad \forall m, t, z \qquad (8)$$

$$\sum_{z=1}^{Z}\sum_{n=F_{tz}}^{L_{tz}}\sum_{m=1}^{M}\sum_{j=1}^{N}(X_{mjn}\, ec_{mj})encost_z + \sum_{z=1}^{Z}\sum_{n=F_{tz}}^{L_{tz}}\sum_{m=1}^{M}\sum_{j=1}^{N}\sum_{i=1}^{N}((ST_{mji}\delta_{mjin})/P_{mjn})\, ec_{mj}encost_z = Tencost_t \qquad \forall t \qquad (9)$$

$$X_{mjn} \leq MW_{mjn} \qquad \forall m, j, n \qquad (10)$$

$$X_{mjn} \leq MY_{mjn} \qquad \forall m, j, n \qquad (11)$$

$$X_{mjn} \geq minim_{mj}(W_{mjn} - W_{mj(n-1)}) \qquad \forall m, j, n = 1 \qquad (12)$$

$$minim_{mj} - \left(X_{mjn} + X_{mj(n+1)}\right) \leq M(1 - Y_{mjn}) \qquad \forall m, j, n \neq L_{TZ} \qquad (13)$$

$$X_{mjn} + X_{mj(n+1)} \geq minim_{mj}(Y_{mjn} - Y_{mj(n-1)}) \qquad \forall m, j, n \neq L_{TZ} \qquad (14)$$

$$X_{mjn} \geq minim_{mj}(Y_{mjn} - Y_{mj(n-1)}) \qquad \forall m, j, n = L_{TZ} \qquad (15)$$

$$\sum_{j=0}^{N} W_{mjn} = 1 \qquad \forall m, n \qquad (16)$$

$$\delta_{mijn} \geq W_{mi(n-1)} + W_{mjn} - 1 \qquad \forall m, i, j = 0, \ldots, N, n \qquad (17)$$

$$\sum_{i=0}^{N}\sum_{j=0}^{N} \delta_{mijn} = 1 \qquad \forall m, n \qquad (18)$$

$$\delta_{m00n} = \sum_{j=0}^{N} \delta_{m0j(n+1)} \qquad \forall m, n = 1, \ldots, K-1 \qquad (19)$$

$$W_{mjn} \leq l_{mj} \qquad \forall m, j, n \qquad (20)$$

$$I_{jt} \geq infin_j \qquad \forall j, t = T \qquad (21)$$

$$W_{mjn}, Y_{mjn}, \delta_{mijn} \in \{0,1\} \qquad \forall m, i, j, n \qquad (22)$$

$$X_{mjn}, I_{jt}, Tencost_t, TX_{jt}, QST_{jt}, PT_{mtz}, TS_{mtz}, rls_{jt} \geq 0 \qquad \forall m, j, n, t, z \qquad (23)$$

According to Eq. (1) of the mathematical model, the total cost of the system is minimized as the first objective function, including the cost of holding, production during and after setup, consumed electrical energy used, and lost sales. Eq. (2) and Eq. (3) indicate the total production amount of product j in the macro-period t during and after setup operations. Eq. (4), the inventory balance equation ensures that the difference between the inventory amounts of product j at the end of t and $(t-1)$ macro-periods is equal to the difference between the sum of production and sales losses and the demand for the product during the macro-period t.

Eq. (5) indicates that the inventory of product j at the macro-period t cannot exceed the total capacity of the silos that the product j is allowed to be assigned. Eqs. (6)- (8) refers that for each machine and each macro-period, the total time of all product-to-product transition operations and production performed in all micro periods of the sub-period z cannot exceed the duration of sub-period z. The total cost of electrical energy consumed in macro-period t is calculated by multiplying the total production amount of all products at all positions during and after setup operation in all machines, the electrical energy consumed by the machines during the production, and the energy price in the sub-period of production is done. Eq. (9) states this calculation.

Eq. (10) and Eq. (11) include the binary variable related to setup (W_{mjn}) and the auxiliary binary variable related to production after setup (Y_{mjn}). These two variables relate to two different conditions. In the minimum batch size constraints of Eqs. (12)- (15), relationships are established between these two variables and X_{mjn}. Therefore, the equations $X_{mjn} \leq MW_{mjn}$ and $X_{mjn} \leq MY_{mjn}$ need to be used for both variables. Eq. (10) and Eq. (11) establish the relation between production and setup variables. Eq. (10) expresses that it is only possible for a product to be produced in a position if it has been set up for it. The big M term in this constraint represents the maximum quantity of a product that can be produced in one machine at one position. Eq. (11) shows that the binary variable Y_{mjn} has to be 1 in order for the product j to be produced on machine m in micro-period n. The setup state of the machines is preserved throughout the idle time. Therefore, setting the variable W_{mjn} to 1 does not guarantee that product j is produced in micro-period n. It shows that machine m is set up for product j in micro-period n. For this reason, in the model, in addition to the setup state, the binary variable Y_{mjn}, which takes the value 1 if product j is produced in micro-period n on the m machine, is also used. Eqs. (12) – (15) are constraints related to minimum lot sizes. Eq. (12) ensures that if the production of product j has just started in the first micro-period (i.e. $W_{mj0} = 0$ and $W_{mj1} = 1$) in machine m, the production amount of product j in the first micro-period is at least as much as the minimum lot size that j product can be produced in m machine. Eq. (13) and Eq. (14) state the total production amount of product j in the n^{th} and the following micro-period in machine m for all micro-periods where n is not the last micro-period of the last macro-period under the following conditions:

-If the production of product j has just started in the n^{th} micro-period in machine m,

- or the production of product j has continued in the n^{th} micro-period after an interruption without switching to another product in machine m

When these conditions are met, the total production amount of product j in the n^{th} and the following micro-period in machine m is at least as much as the minimum batch size of that product in that machine. Eq. (15) states that if product j starts to be produced in the last micro-period of the last macro-period in the m machine, the production amount of product j should be at least the minimum batch size in machine m.

Eq. (16) ensures that a machine can produce only one product type in a micro-period. Product 0 can only be assigned to positions at the beginning of the planning horizon for all machines until the production of an actual product begins. After

the transition from product 0 to an actual product in any position, the transition from actual products to product zero is not allowed. Eq. (17) enforces δ_{mijn} to take the value 1 if machine m produces product i in micro-period $(n-1)$ and changes over to product j in micro-period n. The constraints of Eq. (16) and Eq. (17) ensure that the setup state is preserved on machines as last produced product j (if the production has not started yet, as product 0) during the micro-periods of no production. In this case, δ_{mijn} is forced to take the value 1 for the transition from product j to product j during these micro-periods. For example, if machine m produces product 1 in $(n-1)^{th}$ micro-period and does not make production in n^{th} micro-period, δ_{m11n} and W_{m1n} will be 1.
Eq. (18) guarantees only one transition from product to product for each machine at each position. Eq. (19) indicates that in a position if there is a transition from product 0 to another product in machine m, or if the machine m remains in product 0 state, machine m must have been in product 0 state in the previous position. Thus, when the machine m is set up for an actual product, it is prevented from returning to the product 0 state in later positions. Eq. (20) states that a machine can produce a product in a position only if this product is compatible with this machine. Eq. (21) ensures that the inventory of a product at the end of the last macro-period of the planning horizon is at least the safety stock of that product in this macro-period. Eq. (22) represents binary variables, and Eq. (23) expresses the non-negativity of the other decision variables.
In the model of Koçlar (2005), which was used as a basis in developing the model in this study, unlike this study, overtime was taken into account and lost sales were not considered. The constraints of (10), (16), (17), (18), and (19) in the model in this study are the generalized version of the related single-machine constraints of Koçlar (2005) to m machines. Constraint (4) is a modified version of the inventory balance constraint in Koçlar's (2005) model by adding production made during the setup and the considered lost sales. Constraint (8) was created by subtracting overtime from the capacity constraint in Koçlar's (2005) model.
Although the minimum batch size constraints in the model are structured based on the constraints stated in (3.5) and (3.5') by Koçlar (2005), they are highly changed. In Koçlar (2005)'s model, if there is not enough capacity for the minimum lot size, for only the last position of a macro-period, it is possible to use the next position to meet the minimum lot size. This situation has been stretched in the model of this study, as stated in the constraint explanations.
In the model developed in this study, problem-specific constraints such as sub-periods in which the electrical energy cost differs, the total cost of electrical energy consumed constraint, production during setup, and machine compatibility constraints are included. In addition, safety stock is also taken into consideration.
Figure 4 demonstrates a possible schedule for machine 1 for one day denoted by macro-period t. Suppose that machine 1 is ready to produce product 2 at the beginning of macro-period t. At most, two types of products can be produced in a sub-period. At the beginning of each micro-period, if necessary, a setup is done for the product to be produced. For example, setup is required when switching from product 2 to 1, while it is not required when switching from product 1 to 2. In some positions, the machine may remain idle. The setup state of the machine is preserved throughout the idle time.

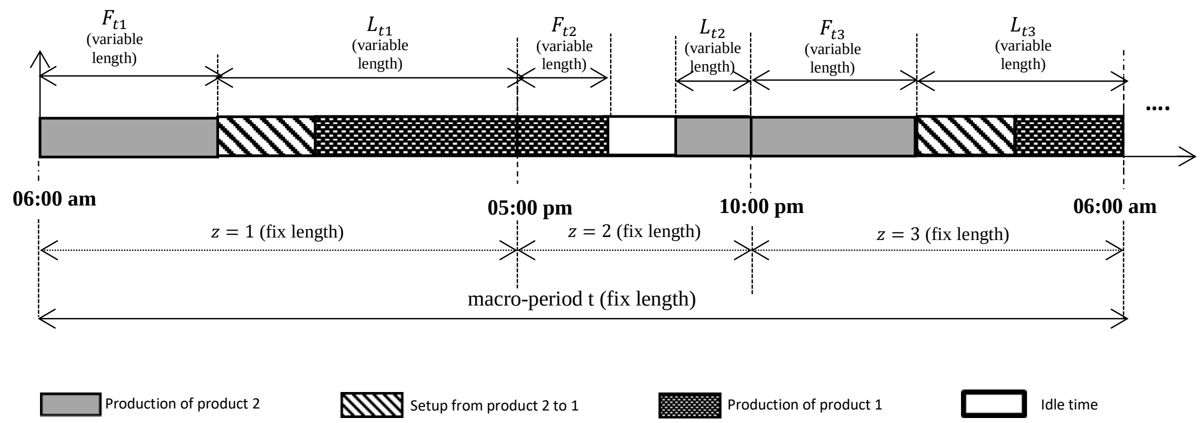

Figure 4. An illustrative example demonstrating a one-day schedule for machine 1

5. Proposed Cyclical Approach

LSM is applied to the real data on the cement grinding process of the analyzed company. The model has been run cyclically for one year. The number of macro-periods in LSM was determined by running LSM with various macro-period numbers and input combinations. The results of these trials were evaluated in terms of solution times. As a result, the number of macro-periods was determined as 5. Cycles, each one 5 days in length (macro-periods $t = \{1,2,\ldots,5\}$), are denoted by $c = C\colon\{1,\ldots,C\}$. As a result, the model has been run in 73 cycles by dividing a year into five-day periods.

In the first cycle, actual inventory amounts of products are used as initial inventories. Then, at the end of cycle c, the initial inventory and safety stocks of products at cycle $c + 1$ are calculated using the sales made each day in cycle c.
Initial inventory of products at cycle $c + 1$ means the product inventory at the end of cycle c is calculated using the rearranged version of Eq. (4).

$$I_{jt}{}^{c} = \begin{cases} I_{j(t-1)}{}^{c} + TX_{jt}{}^{c} + QST_{jt}{}^{c} - s_{jt}{}^{c}, & \text{if } I_{j(t-1)}{}^{c} + TX_{jt}{}^{c} + QST_{jt}{}^{c} - s_{jt}{}^{c} > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4'}$$

where
$s_{jt}{}^{c}$: Sales quantity of product j during the macro-period t at cycle c (ton)
Product safety stocks at each cycle are calculated with a two-step approach by considering demand variations during and 15 days after the cycle period. First, suppose the periods when the production capacity may be insufficient can be predicted, and the production system is prepared accordingly. In that case, the high inventory holding costs caused by continuous high inventory keeping can be prevented. For this purpose, before running LSM for cycle c containing 5 macro-periods, each is 1-day length, the model is run using 3 macro-periods of 5 days for the 15 days just after cycle c. This model is called the Capacity Control Model (CCM). If a capacity inadequacy is predicted for a product for cycle c, in other words, if the lost sales quantity of a product is greater than 0, this amount is added to the calculated safety stock for cycle c. Then, LSM is run using the updated safety stocks for cycle c.
The safety stock of product j at cycle c is calculated by adding the predicted lost sales by CCM to Krupp (1997) 's Mean Absolute Deviation (MAD) based approach formula. $SSMAD_j{}^{c}$ (Safety stock based on MAD of product j at cycle c plus lost sales predicted by CCM for product j at cycle c) and $MAD_j{}^{c}$(MAD for product j at cycle c) formulas are expressed in Eq. (24) and Eq. (25), respectively.

$$SSMAD_j{}^{c} = k(MAD_j^{c-1})\sqrt{LT} + LS_j^{c} \tag{24}$$

where
k: Desired service level multiplier
LT: Lead time
LS_j^c: Lost sales quantity of product j predicted by CCM at cycle c

$$MAD_j{}^{c} = \frac{\sum_{t=1}^{T} |d_{jt}{}^{c} - s_{jt}{}^{c}|}{T} \tag{25}$$

where
$d_{jt}{}^{c}$: Demand for product j in period t at cycle c (ton)
$s_{jt}{}^{c}$: Sales quantity of product j during the macro-period t at cycle c (ton)
T: Number of macro-periods at cycle c
$SSMAD_j{}^{c}$ is used as $infin_j$ in the mathematical model.
When calculating the safety stock for the 1st cycle, the actual sales and forecasted demand 5 days before the period covered by the 1st cycle $(c = 0)$ are used. Lead time is 1 day for all products. The k values for each product group were gradually increased and tested, starting from the 3.2 value specified by Krupp (1997) for 99.5% service level. As a result, the decided values for the products are 8.64, 5.76, 5.76, and 7.2, respectively.
Figure 5 demonstrates the algorithm for the applied cyclical approach. Only model parameters of I_{j0}, $infin_j$ and d_{jt} are updated at each cycle. At cycle c, firstly, CCM is run and LS_j^c is obtained for each product j. By using LS_j^c at the Eq. (24), $SSMAD_j{}^{c}$ is found and used as $infin_j$. I_{j0} is calculated at the end of each cycle c to be used in the next cycle $(c + 1)$. d_{jt} is the demand forecast for the products.
At the beginning of the first cycle $(c = 1)$, CCM is run using the actual inventory quantities of the products as I_{j0} and LS_j^c is obtained as the output of the CCM. $SSMAD_j{}^{c}$, which corresponds $infin_j$, is calculated using LS_j^c. For cycle $c = 1$, LSM is run using model parameters with static values and actual inventory amounts I_{j0}, calculated $infin_j$and d_{jt} inputs. The product inventory amount at the end of cycle c is calculated using the LSM outputs of production quantities during and after setup in Eq. (4').
The product inventory amount at the end of cycle c is calculated by putting the production quantities during and after setup, the LSM output, into Eq. (4'). The product inventory amount at the end of cycle c equals the beginning inventory amounts of products at the cycle $(c + 1)$. If c is less than C, the cycle $(c + 1)$ is started, and all steps starting from the run of the CCM model are repeated. Processes are terminated when c is equal to C.
The value ranges of the model parameters are presented in Table 1.

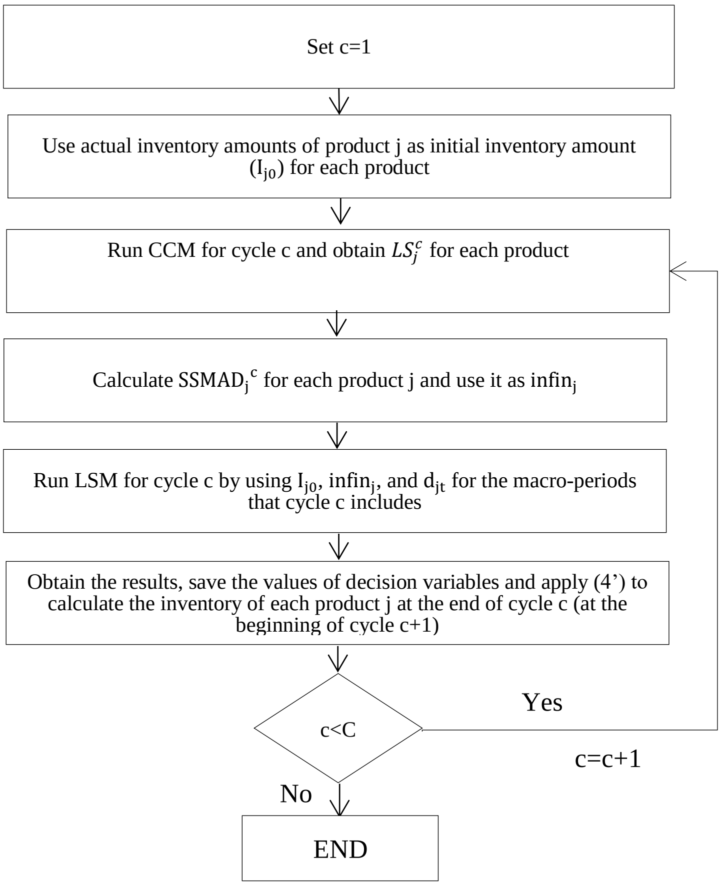

Figure 5. Algorithm for the applied cyclical approach.

Table 1. Model Inputs

Parameters	**Range**
h_j	0.051-0.056
$maxI_j$	2,500-15,000
$minim_{mj}$	280-480
Cap_z	300-660
$encost_z$	0.075-0.332
St_{mij}	30-45
cst_{mj}	46.7 – 74.59
ec_{mj}	38-43
CP_{mj}	43.09-74.59
lsc_j	95.85-118.52

6. Experimental Results

LSM has been run integrated with CCM during a year in 73 cycles containing five-day periods. The reason for running the model for a year is to capture the changes in the factors that affect the model performance in terms of solution time and quality and realistically reveal the model's performance. Model data is updated at the end of each cycle using product sales realized during the current cycle and used in the next cycle. So when the product sales on the last day of a cycle occur, the model can be run for the next cycle. The solution of the model should be obtained in the night to the morning time frame between two consecutive cycles. Therefore, model runtime is restricted to 5 hours. The models are solved with Lingo 9.0 on an Intel Core i7-CPU 2.10GHz 8 Gb Ram Windows7 64-bit PC. LSM has 4,855 variables, 900 of which are binary and 10,412 constraints. In CCM, there are 2655 variables, 540 of which are binary and 4,846 constraints. The models are solved with the Branch-Bound method, one of the exact solution methods.

In 90% of the cycles, the optimum solution was reached within 2 hours and 35 minutes. Even in 23 cycles, the solution time was less than 5 minutes. However, in just 4 cycles, the optimal solution was not reached within 5 hours. In Table 2, the solution times of each cycle are presented.

Table 2. Solution times of cycles

Cycle	**Solution Time**	**Cycle**	**Solution Time**	**Cycle**	**Solution Time**	**Cycle**	**Solution Time**
1	00:00:16	*20*	00:02:46	*38*	00:31:51	*56*	00:00:16
2	00:10:04	*21*	00:11:02	*39*	01:35:15	*57*	00:03:37
3	00:08:06	*22*	00:01:36	*40*	02:24:41	*58*	04:52:22
4	00:05:12	*23*	00:01:54	*41*	00:03:11	*59*	01:02:48
5	00:07:51	*24*	01:35:12	*42*	00:01:34	*60*	01:22:39
6	00:01:05	*25*	00:24:25	*43*	00:02:04	*61*	00:03:48
7	00:16:00	*26*	00:40:10	*44*	*05:00:00*	*62*	00:03:49
8	00:20:01	*27*	00:35:58	*45*	00:28:45	*63*	02:35:00
9	00:21:52	*28*	00:05:11	*46*	*05:00:00*	*64*	00:06:22
10	00:06:00	*29*	00:02:04	*47*	00:01:47	*65*	00:45:11
11	00:03:00	*30*	00:02:05	*48*	00:02:17	*66*	00:08:52
12	00:02:06	*31*	00:03:59	*49*	01:08:12	*67*	00:03:49
13	00:06:05	*32*	04:32:21	*50*	00:07:35	*68*	00:03:08
14	00:18:40	*33*	00:06:18	*51*	*05:00:00*	*69*	01:28:43
15	00:49:32	*34*	01:29:57	*52*	00:10:51	*70*	00:12:47
16	00:32:00	*35*	00:43:14	*53*	01:41:12	*71*	04:54:18
17	02:31:53	*36*	01:37:29	*54*	00:50:54	*72*	*05:00:00*
18	00:19:13	*37*	00:04:51	*55*	00:01:31	*73*	00:37:44
19	00:06:43						

Outputs of the model are compared with the realized firm performance in terms of the total number of setups, total production amount in each machine in each sub-period, utilization time of sub-periods in each machine, and total inventory held during the analyzed year. Also, the total lost sales found by the model is presented. Afterward, each cost item considered in the model is evaluated by a one-to-one comparison with the realized cost.

Table 3. Total number of setups

Machine	**Model**	**Realized**
m=1	12	10
m=2	51	188
m=3	68	136
Total	***131***	***334***

Table 3 compares the model and firm performance regarding the total number of setups. According to the model results, the total number of setups on all machines during the analyzed year is 131, 60.78% less than the firm performed. Depending on the model's output to produce more product $j = 2$ in $m = 1$ than the firm realized, the number of setups in $m = 1$ of the model is higher than realized. On the other hand, in $m = 2$ and $m = 3$, the model has resulted in much fewer setups (72.87% and 50%, respectively) than realized.
The total production amounts in machines in each sub-period found by the model and realized by the firm are given in Table 4. The biggest difference between the model results and the firm performance has occurred in the production amount of $j = 2$ in $m = 1$ and $m = 2$. The model results indicate that $j = 2$ is produced much more at $m = 1$ than the firm realized. While the firm made only 3.74% of all $j = 2$ production in $m = 1$ in the analyzed year, this ratio is 31.06% in

the model. The model's outputs demonstrate that j = 1 is produced less than the quantity produced by the firm at m = 1 and more at m = 2.

Table 4. Total production amounts in machines in each sub-period (ton)

Machine	Sub-period	Model	Realized	Model (after setup)	Realized (after setup)	Model (during setup)	Realized (during setup)
		Product j=1		Product j=2			
m=1	**z=1**	15,943.060	29,479.160	3891.800	776.310	196.290	83.730
m=1	**z=2**	2,226.050	2,266.540	394.850	161.400	28.075	0
m=1	**z=3**	84,661.260	108,724.490	24332.020	2486.160	116.140	201.300
Total		***102,830.370***	***140,470.190***	***28,618.670***	***3,423.870***	***340.505***	***285.030***
m=2	**z=1**	50,269.470	61,520.810	19025.410	11004.440	651.160	850.730
m=2	**z=2**	6,172.730	9,630.750	681.220	1023.410	45.580	0
m=2	**z=3**	121,920.710	75,141.790	42191.620	74605.270	1683.840	7930.700
Total		***178,362.910***	***146,293.350***	***61,898.250***	***86,633.120***	***2,380.580***	***8,781.430***
		Product j=3		Product j=4			
m=3	**z=1**	358,987.860	361,680.660	29,263.480	22,719.870	1,335.130	2,171.050
m=3	**z=2**	35,937.150	78,551.780	2,569.700	1,092.160	64.070	0
m=3	**z=3**	255,869.370	222,279.920	121,144.080	129,988.500	2,934.410	6,516.440
Total		***650,794.380***	***662,512.360***	***152,977.260***	***153,800.530***	***4,333.610***	***8,687.490***

Figure 6-7 demonstrates the model output and realized firm performance of the distribution of total utilization times of sub-periods for each machine during the analyzed year. The model findings show that, for all machines, the ratio of the machines' utilization times at z = 3 to their total utilization times has increased significantly compared to the firm's actual performance. The greatest increase has been experienced in m = 1.

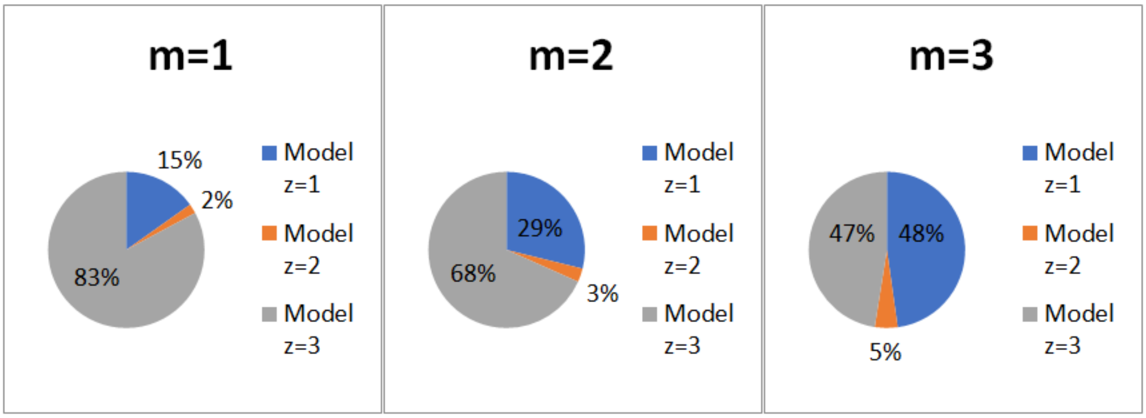

Figure 6. Distribution of utilization times of machines in sub-periods (model)

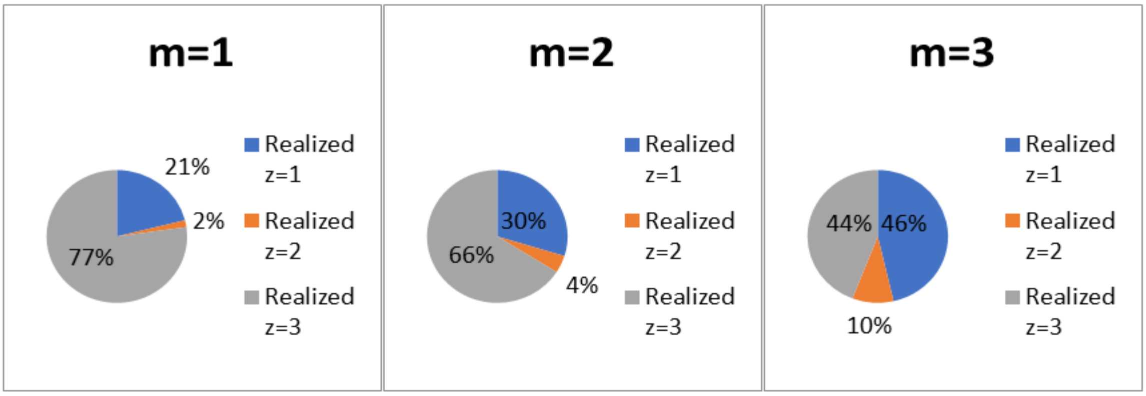

Figure 7. Distribution of utilization times of machines in sub-periods (realized)

According to the model results, during the analyzed year, 47% of $m = 3$'s production time, including during and after setup times, took place in $z = 3$, 48% in $z = 1$, and 5% in $z = 2$. Moreover, compared to the firm's performance at $m = 3$, the model used $m = 3$ more in the cheapest sub-period $z = 3$ and the average cost sub-period $z = 1$. Also, the model has used $m = 3$ significantly less than the firm in the peak cost subperiod $z = 2$.

Table 5. Total end-of-day inventories held throughout the year (ton)

Product	Model	Realized	Change (in percentage)
j=1	1,107,040.900	1,540,565.000	28.14%
j=2	267,998.200	869,073.000	69.16%
j=3	1,010,869.500	2,251,546.600	55.10%
j=4	662,936.800	1,166,342.200	43.16%

During the analyzed year, the model's performance and the firm in terms of the sum of the end-of-day inventory amounts of the products are compared in Table 5. The results show that the model significantly reduces the amount of stock held in the range of 28.14% to 69.16%.

Table 6. Lost sale quantities

Product	Lost sales (ton)	Lost sales/Total annual sales (in percentage)
j=1	5,394.100	1.88%
j=2	929.380	0.94%
j=3	9,483.410	1.43%
j=4	3,034.450	1.87%

The model results indicate that lost sales occurred for all products during the analyzed year by the amount presented in Table 6. With the approach proposed in the study, the decrease in product inventory levels may cause some lost sales. Lost sales of the model indicate the quantities based on the realized sales in the analyzed year. In the analyzed year, the firm’s realized lost sales are unknown. For this reason, a comparison between the model and the firm performance can not be made. Even for $j = 4$, which has the highest ratio of lost sales to total annual sales, this rate is 1.87%. Therefore, the performance of the model might be interpreted as successful in terms of lost sales amounts, considering that only the actual inventory quantities of the products, the demands, and the calculated safety stock quantities are updated in each cycle without taking into account other variables that may affect the process.

The one-to-one comparison of each cost item considered in the model with the actual cost is presented in Table 7. Costs are not presented in monetary units due to confidentiality reasons related to the company. Instead, the firm's total cost for items considered during the analyzed year has been used as 100 units, and the values of all cost items have been written proportionally to these 100 units.

Table 7. Comparison of model results and firm performance in terms of each cost item

Cost items	Model (in percentage)	Realized (in percentage)	Reduction in cost (in percentage)
Inventory holding	0.23	0.43	47.51%
Production during the setups	0.56	1.49	62.54%
Production after the setups	87.77	89.1	1.49%
Electrical energy	8.21	8.98	8.65%
Lost sales	2.87	0	-
Total	99.63	100	0.37%

Table 7 indicates that the firm's actual total cost is 100 units, while the model's total cost is 99.63 units. For example, if the firm's actual cost is 100000 TL, the actual cost of the model is 99628.40 TL. Realized inventory holding cost is 0.43% of the realized total cost, while the model's inventory holding cost is 0.23% of the realized total cost. The model has provided a cost reduction of 1.49% in the production after the setups item, which has the largest share of the total cost. The model has achieved a significant cost reduction of 8.65% in electrical energy, the second largest cost item. The highest rate of cost improvement has been achieved in the cost of production during the setups. The lost sales cost of the firm is seen as 0 in Table 7 because the firm's realized lost sales in the analyzed year are unknown. Therefore, it constitutes a limitation of this study. However, the lost sales of the model found based on the firm's realized sales in the analyzed year is an indicator that may be a reflection of the decrease in stock levels obtained with the model. Considering all cost items, the application of LSM integrated with CCM with the proposed cyclical approach during the analyzed year has achieved a cost reduction of 0.37%, whose monetary value corresponds to a quite significant amount.

7. Sensitivity Analysis

Sensitivity analysis has been conducted to reveal the sole effects of minimum batch size, production time, and setup time parameters on the total cost. In the experiments, current parameter values have been used as the baseline. The baseline values have been multiplied by the factors whose values are derived from 0.10 to 1.90 by increasing 0.10 to evaluate the effects of the two-sided changes in parameter values on the total cost. The model was run for 10 randomly selected cycles, and the minimum, maximum, and average cost reduction and cost increase percentages were determined. The results of the sensitivity analysis are presented in Table 8.

Production time has the most significant effect on the total cost among the parameters discussed. A 10% reduction (factor 0.9) in production times of all products on all machines has reduced the total cost by an average of 0.6249%. As the production time decreases, the total cost continues to decrease. Reducing the production time between 70% and 90% (factor 0.3-0.1) has almost the same effect on the total cost. On the other hand, increasing production time by degrees creates more considerable increases in total cost. The results indicate that the changes in the setup time do not significantly affect the total cost. Although reducing the minimum batch sizes of the products does not significantly affect cost reduction, it is seen that increasing the minimum batch sizes significantly increases the cost.

Table 8. The results of sensitivity analysis

	Cost Reduction (%)				Cost Increase (%)			
Parameters	**Factor**	**Min**	**Max**	**Average**	**Factor**	**Min**	**Max**	**Average**
Minimum batch size	*0.90*	0.0000%	0.0148%	0.0036%	*1.10*	0.0395%	0.6693%	0.4151%
	0.80	0.0000%	0.0436%	0.0177%	*1.20*	0.1489%	0.8201%	0.4677%
	0.70	0.0000%	0.0441%	0.0201%	*1.30*	0.2141%	2.0699%	1.0397%
	0.60	0.0000%	0.0489%	0.0222%	*1.40*	0.4573%	5.5531%	1.5662%
	0.50	0.0000%	0.0588%	0.0267%	*1.50*	1.2487%	6.4181%	3.9589%
	0.40	0.0000%	0.0600%	0.0273%	*1.60*	1.8703%	6.4181%	4.2741%
	0.30	0.0000%	0.0602%	0.0275%	*1.70*	1.9314%	6.4181%	4.2970%
	0.20	0.0002%	0.0611%	0.0276%	*1.80*	3.0347%	13.0701%	9.6043%
	0.10	0.0004%	0.0623%	0.0278%	*1.90*	7.1098%	13.0701%	10.5653%
Production time	*0.90*	0.0141%	1.9204%	0.6249%	*1.10*	0.3392%	6.2254%	1.5648%
	0.80	0.0162%	3.1206%	1.1758%	*1.20*	0.7892%	10.8375%	3.1582%
	0.70	0.0376%	3.6772%	1.6881%	*1.30*	1.1848%	15.3922%	5.1036%
	0.60	0.0376%	4.2099%	2.2404%	*1.40*	1.8266%	20.5083%	7.4425%
	0.50	0.0376%	4.9120%	2.8046%	*1.50*	2.3738%	25.6748%	12.7996%
	0.40	0.0376%	5.9631%	3.2112%	*1.60*	2.6365%	30.6002%	15.5483%
	0.30	0.0376%	7.0173%	3.4210%	*1.70*	3.2033%	34.3009%	18.3204%
	0.20	0.0376%	7.0639%	3.4498%	*1.80*	13.4537%	41.7720%	24.7486%
	0.10	0.0376%	7.0874%	3.4526%	*1.90*	14.1031%	44.4954%	27.3967%
Setup time	*0.90*	0.0000%	0.0080%	0.0040%	*1.10*	0.0000%	0.0070%	0.0036%
	0.80	0.0000%	0.0175%	0.0089%	*1.20*	0.0000%	0.0140%	0.0076%
	0.70	0.0000%	0.0276%	0.0148%	*1.30*	0.0000%	0.0434%	0.0139%
	0.60	0.0000%	0.0363%	0.0198%	*1.40*	0.0000%	0.0784%	0.0206%
	0.50	0.0000%	0.0447%	0.0246%	*1.50*	0.0000%	0.0957%	0.0256%
	0.40	0.0000%	0.0541%	0.0308%	*1.60*	0.0000%	0.0983%	0.0292%
	0.30	0.0000%	0.0658%	0.0371%	*1.70*	0.0000%	0.1011%	0.0332%
	0.20	0.0000%	0.0775%	0.0429%	*1.80*	0.0000%	0.1039%	0.0359%
	0.10	0.0000%	0.0911%	0.0495%	*1.90*	0.0000%	0.1065%	0.0383%

8. Conclusion

This study aimed to prepare feasible, applicable, and minimum cost schedules for cement mills by considering the unique and industry-specific characteristics of the cement grinding process. In order to create practically applicable minimum cost schedules, it is necessary to anticipate the capacity deficiencies that may arise due to the variability in the industry's demand structure and adjust the products' inventory levels accordingly. From this point of view, this study proposed an approach that integrates lot sizing and scheduling with adjusting inventory levels considering the anticipated capacity deficiencies. The basis of the proposed approach was to run the models of LSM and CCM cyclically. The models were developed based on the GLSP with a modification of the time representation scheme. Among the process and industry-specific characteristics, time-varying electricity pricing, alternative recipes, sequence-dependent setup times, and varying production times were considered in the models.

While developing the proposed approach, the primary focus was on practical applicability rather than solution time. This approach was applied in one year by using the actual data of a firm operating in the cement industry and compared with the realized performance to test the proposed approach's applicability. Model runtime was restricted to 5 hours, considering the time between two consecutive cycles. In only 4 cycles among 73, the optimal solution was not reached within 5 hours. In 23 cycles, the optimal solution was obtained in less than 5 minutes. The solution time indicated that the model provided the required performance in terms of solution time for the problem considered.

LSM was run integrated with CCM for a year in 73 cycles containing five-day periods. The proposed approach significantly reduced setup costs, inventory holding costs, electrical energy costs, and production after-setup costs. The model achieved a 47.51% cost reduction in inventory holding, 62.54% in production during setups, 1.49% in production-after-setups, and 8.65% in electrical energy. Although the lost sales were considered in the model, since the lost sales of the firm were not known in the problem addressed, the model and firm performance could not be compared correctly. This situation created a limitation for the study. In comparing the model and firm performance, although the firm's lost sales were considered 0, a 0.37% reduction in cost was obtained with the model.

In energy-intensive processes such as cement production, a significant amount of energy can be saved by effectively scheduling cement mills and determining product lot sizes. Therefore, significant contributions to energy cost reduction and sustainable development might be provided.

Sensitivity analysis was conducted to gain managerial insights by examining how much minimum batch size, production time, and setup time affect the total cost. The sensitivity analysis results indicated that a reduction in production time significantly affected the total cost. For example, even a 10% decrease in the production time provided a 0.6249% average and a 1.9204% maximum reduction in the total cost. This result indicated that the investments to increase the production capacity would significantly contribute to reducing the total cost. On the other hand, improvements in minimum batch size and setup time did not significantly affect the total cost. It was determined that the total cost would significantly increase if there were an increase in production time and minimum batch size especially in production time. Therefore, it may be deduced that any unplanned interruptions or disruptions in the production process that would increase production time or decrease capacity and any practice requiring increasing the minimum batch size should be avoided.

Although this study includes many characteristics specific to the cement industry, most are also typical in the process industries. Therefore, the approach and LSM proposed in this study might be adaptable to process industries with similar characteristics. In future studies, instead of the CCM approach applied for capacity inadequacy prediction in this study, a machine learning-based prediction model can be developed using parameters such as product inventory levels, demand forecasts, and capacity utilization rates for the past periods.

Disclosure statement

The authors reported no potential conflict of interest

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