

# A Linear-Programming–Driven Two-Level Factorial Design for Cost-Efficient Alternative Fuel Experiments in a Simulated Cement Calciner

Pongchanun Luangpaiboon<sup>1</sup>, Sirirat Juttijudata<sup>2,\*</sup>

<sup>1</sup>*Industrial Statistics and Operational Research Unit (ISO-RU), Faculty of Engineering, Thammasat School of Engineering, Thammasat University, Pathum Thani 12120, Thailand*

<sup>2</sup>*Applied Optimization Research Unit, Department of Industrial Engineering, Faculty of Engineering Sriracha, Kasetsart University, Chonburi 20130, Thailand*

Received 31 January 2026; Received in revised form 28 February 2026

Accepted 30 March 2026; Available online 30 June 2026

## ABSTRACT

The cement industry is among the most energy-intensive sectors and a major contributor to global CO<sub>2</sub> emissions. Although increasing alternative fuel (AF) utilization in calciner operation can reduce coal consumption, laboratory-scale screening of multiple AFs is costly. This study proposes a mathematical framework that embeds a two-level full factorial design within a Linear Programming (LP) model to generate an economically optimized experimental plan under energy constraints. For a given number of AF factors  $K$ , the model (i) assigns Low–High usage levels to each AF, (ii) constructs the complete  $2^K$  factorial design, (iii) computes the Mixed Coal (MC) required in each treatment to satisfy the target  $NCV_{as-received}$ , and (iv) minimizes the total cost of executing the full factorial design. The LP formulation incorporates decision variables for AF and MC quantities, subject to limits on total AF mass, minimum Low–High separation, and separate line calciner energy requirements. A five-AF case study demonstrates that the optimized 32-run design satisfies all constraints while achieving approximately 41–42% coal substitution relative to pure-coal operation at the same  $NCV_{as-received}$ . The results confirm that the proposed framework provides a general, cost-aware planning tool for factorial mixture experiments and is readily extendable to other energy and engineering systems.

**Keywords:** Alternative fuels; Cement calciner; Experimental design optimization; Linear programming; Mixture experiments; Two-level factorial design

## 1. Introduction

The cement industry is among the most energy-intensive manufacturing sectors and a major contributor to global CO<sub>2</sub> emissions, largely due to limestone calcination and the combustion of fossil fuels, particularly coal, to achieve kiln and calciner temperatures. Although alternative fuels (AFs) are increasingly promoted, coal still dominates thermal energy supply in most plants. With tightening environmental regulations and volatile fuel prices, cement producers are under growing pressure to increase AF substitution in a technically reliable and economically viable manner, which requires quantitative tools for evaluating AF options at both laboratory and industrial scales.

The Separate Line Calcliner (SLC) is well suited for AF utilization because of its long residence time, lower oxygen demand, and ability to process diverse fuels such as biomass, rice husk, municipal solid waste (MSW), wood residues, and refuse-derived fuels. Their application is constrained by as-received net calorific value  $NCV_{as-received}$ , moisture, chlorine and sulfur content, ash characteristics, and unit cost. At laboratory scale, testing multiple AFs and their mixtures entails substantial expense for fuel preparation, calorific measurements, and simulation of SLC conditions. As the number of factors increase, the number of experiments in a full factorial design grows exponentially, motivating the use of mathematical optimization to support experimental planning under cost and energy constraints.

Recent studies primarily address combustion behavior and environmental impacts of AFs. Low-temperature co-gasification of rice husk and waste tires has been investigated to identify synergistic effects and operating conditions

that enhance gas quality [1]. Laboratory measurements of NO<sub>3</sub>, SO<sub>2</sub>, CO, and CO<sub>2</sub> emissions have been used to assess the decarbonization potential of mixed AF streams [2]. Neural-network models have been applied to chemical-looping gasification and co-combustion of rice husk and textile waste to predict syngas composition and efficiency [3]. Review papers emphasize the role of advanced design-of-experiments (DoE) methods, including factorial design, response surface methodology (RSM), and Taguchi techniques, in optimizing combustion parameters and reducing environmental impact [4].

From a system perspective, supply-chain and resource-availability studies highlight the difficulty of ensuring stable AF supply. Forecasting analyses of rice-husk availability stress the need for resilient biomass supply chains [5], while investigations of MSW management link cement AF demand with logistical and economic barriers to large-scale RDF use [6]. Circular-economy assessments indicate that AF adoption can lower CO<sub>2</sub> emissions and operating costs without degrading kiln performance [7, 8], and regional case studies report both environmental benefits and operational challenges due to fuel heterogeneity [9–10]. Empirical analyses further confirm that higher AF substitution rates correlate strongly with reduced CO<sub>2</sub> emissions in cement plants [11]. Some studies apply multi-objective optimization to raw-mix design and AF blending [12], but they focus mainly on continuous kiln operation rather than laboratory-scale experimentation.

DoE and optimization techniques are also widely applied in cementitious materials and waste-valorization research. RSM, central composite, Box–Behnken, and D-

optimal designs have been used for concrete and geopolymers systems incorporating various industrial by-products [13–17], while metaheuristic methods such as Gray Wolf Optimization and genetic algorithms have been employed for complex mixture optimization [18]. Beyond the cement sector, linear and multi-objective optimization frameworks support techno-economic analyses of sustainable aviation fuels, hydrogen systems, and waste-to-energy pathways [19–25], as well as slag and dust utilization in metallurgical processes [26, 27]. However, these studies rarely integrate economic optimization directly with full factorial experimental design.

This study addresses this gap by embedding a two-level full factorial design within a linear programming (LP) framework. For  $K$  fuels, all  $2^K$  Low–High combinations are generated to capture main and interaction effects, while the LP model minimizes total experimental cost subject to constraints on AF mass,  $NCV_{as-received}$ , and thermal requirements of a simulated SLC. The model converts factor levels into fuel masses, determines the required mixed-coal supplementation for each treatment, and verifies feasibility and energy balance across the entire factorial set.

By integrating optimization into the DoE stage, the framework enables advance estimation of experimental cost, identification of feasible AF ranges, and design of statistically robust yet economically efficient test programs. A numerical case study with five AFs demonstrates a 32-run factorial plan that satisfies all constraints while substantially reducing coal usage. The remainder of the paper is organized as follows: Section 2 presents the factorial and LP formulation, Section 3 discusses the numerical results and scalability, and Section 4 concludes with perspectives for future re-

search.

## 2. Related Method

This study applies an integrated framework that combines alternative fuel (AF) screening, a two-level full factorial design, and a linear programming (LP) cost model to plan laboratory-scale AF experiments for a simulated Separate Line Calciner (SLC). The procedure begins by identifying available AFs and screening them based on their as-received net calorific value ( $NCV_{as-received}$ ) to ensure compliance with minimum SLC energy requirements. Five AFs that satisfy these criteria are selected as experimental factors. Each fuel is then assigned two practical operating levels (Low and High), representing realistic laboratory usage ranges and their corresponding costs.

With five factors at two levels, a full  $2^5$  factorial design is constructed, resulting in 32 experimental treatments covering all possible AF combinations. Before any laboratory work is conducted, the complete factorial matrix is embedded in an LP model to estimate the total cost of executing all 32 runs. The LP formulation accounts for fuel prices at both levels and enforces technical constraints, including minimum  $NCV_{as-received}$  and a maximum AF mass per treatment. This allows the total experimental budget to be evaluated in advance, enabling cost-aware planning while preserving the statistical structure of the design.

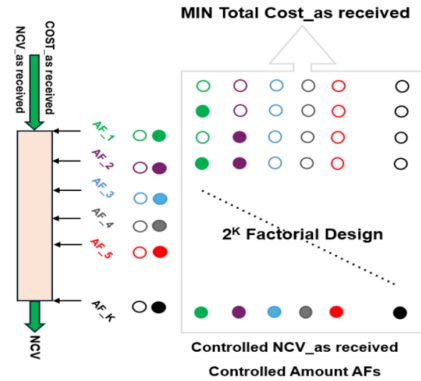
In classical design of experiments, three core principles—randomization, replication, and blocking—are used to control nuisance variation and ensure valid statistical inference. In this study, the proposed framework focuses on the economic planning of a two-level full factorial design rather than on executing and analyzing the physical experiments themselves.

Accordingly, the LP model is constructed under the assumption of one planned run per treatment (no replication) and does not explicitly incorporate randomization or blocking variables; it optimizes Low–High factor levels and computes the cost of implementing the complete  $2^K$  factorial structure under AF-mass and  $NCV_{as-received}$  constraints. In a subsequent laboratory phase, the 32 factorial runs generated by the model can be randomized in execution order to guard against time-related biases, replicated for selected treatments (e.g., centre or corner points) to estimate experimental error, and blocked if practical constraints (such as different days, batches, or furnace conditions) introduce structured nuisance factors. Thus, the present work provides the economic and mathematical design of the factorial plan, while the traditional DOE principles of randomization, replication, and blocking are intended to be applied at the implementation and analysis stages of the physical SLC experiments.

The proposed approach therefore provides a unified decision-support tool that links technical feasibility, statistical rigor, and economic evaluation. AFs are first screened using objective calorific criteria, then systematically arranged in an orthogonal two-level factorial design, and finally assessed through LP under realistic SLC energy demands. In this way, laboratory fuel selection and test planning are transformed from a trial-and-error process into a quantitative optimization problem, allowing cement plants to compare testing scenarios, control experimental cost, and design practical and statistically sound AF evaluation programs (Fig. 1).

## 2.1 Two-level factorial design

To evaluate the influence of selected alternative fuels (AFs) under simulated



**Fig. 1.** Stepwise framework integrating AF screening, two-level factorial design, and LP-based cost optimization for planning laboratory-scale AF evaluations under SLC energy requirements.

SLC conditions, a two-level full factorial design is adopted. Each AF is defined at two operating levels, Low and High, representing realistic differences in fuel dosage, handling, and cost at laboratory scale. Using two levels per factor allows simultaneous identification of main effects (individual fuel influence) and interaction effects (combined influence of fuels). Such interactions are important in SLC combustion, where heterogeneous materials such as biomass, refuse-derived fuels, and carbonaceous residues often exhibit non-additive behavior.

For the five AFs selected based on  $NCV_{as-received}$  compliance, the full design consists of  $2^5 = 32$  treatment combinations. Each treatment represents a unique Low–High configuration and forms part of an orthogonal and balanced design. The factor levels are encoded in binary form (0 for Low, 1 for High) to allow direct integration with the linear programming (LP) model. This encoding preserves orthogonality and supports unbiased estimation of both main and interaction effects, which is essential when studying the combined impact of mul-

tiple heterogeneous fuel streams.

A full factorial design is particularly suitable at the screening stage, as it explores the entire factor space using only two discrete levels and avoids the need for intermediate or gradient-based testing. This is valuable given the wide variation in AF properties such as moisture, ash content, and volatility, all of which can strongly affect thermal behavior. By systematically enumerating all Low–High combinations, the design provides a statistically sound basis for identifying promising AF mixtures for further optimization.

Although the present work focuses on economic planning rather than immediate combustion experiments, construction of the complete two-level factorial matrix is necessary. The matrix serves as the structural input to the LP model, which estimates the total cost of performing all 32 treatments, including AF usage and supplementary coal demand. Linking the economic evaluation directly to the factorial structure ensures that cost estimation remains consistent with statistical rigor, operational realism, and SLC-specific technical constraints.

## **2.2 Linear programming**

The linear programming (LP) model developed in this study serves as an economic planning tool to estimate the total cost of executing a complete two-level factorial design with  $K$  alternative fuels (AFs). In such a design, each fuel is tested at two levels, Low and High, resulting in  $2^K$  treatment combinations. As  $K$  increases, the number of experiments and the associated material cost grow rapidly. The proposed LP model organizes this cost evaluation by combining AF unit prices, the factorial structure, and SLC-related technical constraints within a single optimization frame-

work.

The model is based on the factorial indicator  $a_{ij}$ , which specifies whether  $AF_i$  is set at the Low (–1) or High (+1) level in treatment  $j$ . These indicators are taken directly from the two-level factorial matrix and can be generated for any number of AFs. Using this binary information, the LP assigns the corresponding Low- or High-level cost of each AF to every treatment. In this way, variations in calorific value, moisture, heterogeneity, and procurement cost among different AFs are consistently reflected in the total experimental cost.

Industrial feasibility is enforced through a constraint requiring each AF to satisfy the minimum as-received net calorific value,  $NCV_{as-received}$ , for SLC operation. A binary screening variable activates an AF in the model only if this criterion is met. Fuels that do not reach the required  $NCV_{as-received}$  are excluded from the cost calculation, even if they appear in the factorial structure. This ensures that the estimated cost corresponds to realistic operating conditions and avoids allocating resources to technically unsuitable fuels.

The objective function of the LP minimizes the total cost of performing all  $2^K$  treatments. While the factorial design defines the complete set of Low–High combinations, the optimization framework allows systematic comparison of different scenarios, such as changing the number of AFs or their level assignments, before any laboratory procurement or testing is carried out. The model therefore acts as a decision-support tool for evaluating the economic impact of alternative experimental plans, for example when comparing designs with  $K - 4$  and  $K - 6$  fuels.

Overall, the LP-based framework provides a scalable and quantitative approach for planning AF experiments. It au-

tomatically adapts to the chosen number of factors, evaluates the cost of all factorial combinations, and enforces  $NCV_{as-received}$ , eligibility. By integrating factorial design with economic optimization, the model supports the development of laboratory programs that are both statistically rigorous and economically feasible, and it forms the basis for the detailed mathematical formulation presented in the next section.

### 2.3 A novel LP-embedded factorial model for economic planning of AF laboratory experiments

The Linear Programming (LP) model proposed in this study provides a decision-support framework for planning Alternative Fuel (AF) experiments before laboratory testing. Unlike conventional cost models that assume fixed fuel quantities, the LP formulation determines the optimal Low and High levels of each AF while enforcing mass and energy constraints for every treatment in a  $2^K$  factorial design. This allows the statistical structure of the design, material feasibility, and economic impact to be evaluated within a single integrated model, which has not been addressed in previous AF studies for cement applications.

Each  $AF_i$  (for  $i = 1, 2, \dots, K$ ) is associated with two decision variables: the Low-level quantity  $L_i$  and the High-level quantity  $H_i$ . These variables are subject to laboratory limits, including maximum allowable mass and a minimum separation constraint  $H_i - L_i \geq d$  to ensure sufficient contrast between  $H_i - L_i$  factor levels. The factorial indicator  $a_{ij} \in \{-1, +1\}$ , obtained from the two-level factorial matrix, assigns the appropriate Low or High level to each treatment  $j$ . This mapping preserves orthogonality of the design while ensuring that all treatments are constructed from feasible fuel ranges. The model also includes

a total AF mixture constraint  $\sum_{i=1}^K x_{ij}$ , representing the maximum AF mass allowed in one laboratory run. Energy feasibility is enforced by calculating the Mixed Coal (MC) required to reach the target thermal input  $E_{target}$ . For each treatment, the energy provided by AFs is denoted by  $E_{AF,j}$ , and the required coal supplement is given by

$$MC_j = \max \left( 0, \frac{E_{target} - E_{AF,j}}{EN_{MC}} \right); \forall j. \quad (2.1)$$

The total cost of each treatment is then computed by combining AF material costs and coal consumption,

$$Cost_j = \sum_{i=1}^K C_i x_{ij} + C_{MC} MC_j; \forall j, \quad (2.2)$$

and the overall objective is to minimize the cumulative cost over all  $2^K$  treatments,

$$\min \sum_{j=1}^{2^K} Cost_j. \quad (2.3)$$

By linking continuous AF level selection, factorial treatment structure, mass limits, calorific balance, and total experimental cost in one framework, the LP model transforms factorial design from a purely statistical tool into an economic planning instrument. It enables laboratories and cement plants to estimate the full cost of a complete factorial campaign, compare scenarios with different numbers of AF factors, and design experiments that are both statistically sound and economically feasible. The notation used in the model is summarized in Table 1.

The economic planning problem is finally expressed as a finite-dimensional linear program with decision variables  $L_i, H_i, x_{ij}$ , and  $MC_j$ . All constraints are linear and all cost terms are affine, so

**Table 1.** Parameters and their notations.

| Parameter           | Notation                                                              |
|---------------------|-----------------------------------------------------------------------|
| $K$                 | Number of Alternative Fuels (AFs)                                     |
| $i = 1, \dots, K$   | Index AFs                                                             |
| $j = 1, \dots, 2^K$ | Index factorial treatments                                            |
| $L_i, H_i$          | Low and High levels of $AF_i$ (decision variables)                    |
| $x_{ij}$            | Grams of $AF_i$ used in treatment $j$                                 |
| $a_{ij}$            | Factorial level indicator                                             |
| $MC_j$              | Grams of Mixed Coal required in treatment $j$                         |
| $C_i, C_{MC}$       | Cost per gram of $AF_i$ and Mixed Coal                                |
| $EN_i, EN_{MC}$     | NCV <sub>as-received</sub> (energy) per gram of $AF_i$ and Mixed Coal |
| $E_{\text{target}}$ | Required SLC energy per treatment                                     |
| $AF_{\text{max}}$   | Maximum allowable AF mass per treatment                               |
| $d$                 | Minimum separation between Low and High levels                        |
| $LB_i, UB_i$        | Lower and upper bounds for $AF_i$                                     |

the model can be solved using standard LP solvers. The factorial structure enters through the fixed binary parameters  $a_{ij} \in \{-1, +1\}$  defined by the  $2^K$  design matrix. The resulting LP-embedded factorial planning problem is written as LP-embedded two-level factorial experimental-planning problem:

$$\text{Min} Z = \sum_{j=1}^{2^K} \left( \sum_{i=1}^K C_i x_{ij} + C_{MC} MC_j \right) \quad (2.4)$$

S.T.

$$\sum_{i=1}^K x_{ij} \leq AF_{\text{max}}; \quad \forall j \quad (2.5)$$

$$x_{ij} = \frac{(H_i + L_i) + a_{ij}(H_i - L_i)}{2}; \quad \forall i, j \quad (2.6)$$

$$MC_j \geq \frac{(E_{\text{target}} - E_{AF,j})}{EN_{MC}}; \quad \forall j \quad (2.7)$$

$$E_{AF,j} = \sum_{i=1}^K EN_i x_{ij}; \quad \forall j \quad (2.8)$$

$$\sum_{i=1}^K H_i \leq AF_{\text{max}} \quad (2.9)$$

$$H_i - L_i \leq d; \quad \forall i \quad (2.10)$$

$$MC_j \geq 0; \quad \forall j \quad (2.11)$$

$$LB_i \leq L_i \leq H_i \leq UB_i; \quad \forall i \quad (2.12)$$

$$a_{ij} \in \{-1, +1\}; \quad \forall i, j \quad (2.13)$$

Eq. (2.4) defines the objective: the total cost ( $Z$ ) is the sum, over all treatments  $j$ , of AF material costs  $\sum_i C_i x_{ij}$  and the Mixed Coal cost  $C_{MC} MC_j$ . Eq. (2.5) enforces the mass constraint per treatment, requiring the total AF mass to be at most  $AF_{\text{max}}$  ( $\leq 18$  g). Eq. (2.6) maps the coded factorial levels  $a_{ij}$  to real AF masses  $x_{ij}$  between  $L_i$  and  $H_i$ . This is the standard linear transformation from -1,+1 to physical Low–High levels used in two-level designs. Eq. (2.6) maps the coded factorial levels  $a_{ij}$  to real AF masses  $x_{ij}$  between  $L_i$  and  $H_i$ . This is the standard linear transformation from -1,+1 to physical Low–High levels used in two-level designs. Eq. (2.7) maps the coded factorial levels  $a_{ij}$  to real AF masses  $x_{ij}$  between  $L_i$  and  $H_i$ . This is the standard linear transformation from -1,+1 to physical Low–High levels used in two-level designs.

Eq. (2.8) computes the energy contributed by AFs in treatment  $j$  as the sum of AF masses times their NCV<sub>as-received</sub>. Eq. (2.9) ensures that the sum of all High levels does not exceed the allowable AF mass per treatment, guaranteeing feasibility when all factors are at their High settings. Eq. (2.10) imposes the minimum Low–High separation  $d$  for each AF, which is required for a meaningful two-level factorial contrast in laboratory practice. Eq. (2.11) is the non-negativity constraint for Mixed Coal. Eq. (2.12) constrains Low and High AF levels within practical plant bounds  $[LB_i, UB_i]$ . Eq. (2.13) defines the binary factorial structure, fixing each  $a_{ij}$  at -1 (Low) or +1 (High) according to the pre-specified  $2^K$  design matrix.

In the present work, the LP model

is formulated with cost minimization as the single objective and without an explicit upper bound on the total budget. The model therefore returns the minimum feasible cost of executing the complete  $2^K$  factorial design under the AF-mass and energy constraints. In practice, this minimum cost can be compared ex post with the plant's available experimental budget; if the available budget is lower, the decision maker may reduce the number of AF factors  $K$ , switch to a fractional factorial design, or relax some experimental requirements. Thus, in this study the LP model is used primarily as an economic estimation and planning tool, rather than as a strict budget-feasibility filter.

### 3. Results and Discussion

The purpose of the numerical experiments is not to calibrate a specific industrial plant, but to illustrate the performance of the proposed model using realistic parameter values. The alternative fuel (AF) unit costs and  $NCV_{as-received}$  data are taken from an industrial case; however, all calculations are carried out on the LP formulation itself. The model is therefore generic and remains applicable to any number of fuels  $K$ , any lower and upper bounds ( $LB_i, UB_i$ ), and any set of cost and  $NCV_{as-received}$  values.

#### 3.1 General behavior of the proposed model for different numbers of AF factors

Although the case study considers five alternative fuels (AFs) ( $K = 5$ ) in a  $2^5$  two-level factorial design, the proposed framework is general and can be applied to any number  $K$  and to different AF portfolios. For a given  $K$ , the model determines the Low and High levels ( $L_i, H_i$ ) of each AF within plant-defined bounds, enforces a minimum separation  $d$ , and generates the

complete  $2^K$  design. Constraints on the total AF mass per treatment and on the target  $NCV_{as-received}$  ensure that all combinations are experimentally feasible and thermally realistic for SLC operation. Mixed Coal (MC) is then introduced only to compensate for any energy deficit between the AF mixture and the target thermal input. The objective function aggregates the cost of AFs and MC over all  $2^K$  runs, producing an experimental plan that is both statistically consistent and economically explicit.

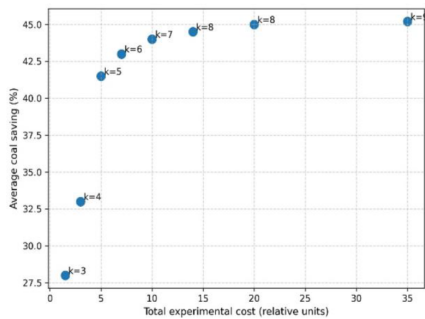
To illustrate the general behavior of the model, Table 2 reports representative results for several hypothetical cases with  $K = 3, 4, 5, 6$ . Each case assumes a different set of AFs with realistic, but problem-specific,  $NCV_{as-received}$  and cost data. The model computes feasible Low-High levels, AF mixture quantities, MC requirements, and the total cost of performing all  $2^K$  experiments. The reported values are intended to show typical trends and scaling effects rather than to represent a particular plant. The detailed  $K = 5$  case corresponds to the practical example discussed in the previous subsections.

This general analysis reveals several key trends. First, the number of treatments increases as  $2^K$ , so the required laboratory runs and total material consumption grow rapidly with the number of AF factors. Even if the AF and Mixed Coal usage per run remain similar, the cumulative experimental cost rises significantly. Second, coal substitution improves when more AFs with favorable  $NCV_{as-received}$  and cost characteristics are included (for example, when moving from three to five factors), because the optimization gains more flexibility to replace coal. Third, the  $K = 5$  case represents a practical compromise: it is sufficiently complex to capture interaction effects and achieve substantial coal reduction

**Table 2.** Illustrative behavior of the proposed model for different numbers of AF factors  $K$ .

| Case                                     | A                                                                       | B                                                                                         | C (case study)                                                                                             | D                                                                                                        |
|------------------------------------------|-------------------------------------------------------------------------|-------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------|
| Number of AF factors ( $K$ )             | 3                                                                       | 4                                                                                         | 5                                                                                                          | 6                                                                                                        |
| Number of treatments ( $2^K$ )           | 8                                                                       | 16                                                                                        | 32                                                                                                         | 64                                                                                                       |
| Typical AF mass per treatment (g)        | 12–15                                                                   | 15–17                                                                                     | 17.5–17.9                                                                                                  | 17.5–18.0                                                                                                |
| Typical MC usage per treatment (g)       | 16–18                                                                   | 15–17                                                                                     | 14.2–14.5                                                                                                  | 13.5–15.0                                                                                                |
| Approximate coal saving vs pure coal (%) | 25–35                                                                   | 30–40                                                                                     | 41–42                                                                                                      | 40–45                                                                                                    |
| Qualitative cost profile                 | Low total cost; small design                                            | Moderate cost; manageable design size                                                     | Total cost $\approx$ 3.28 million THB; narrow cost band per run                                            | High total cost; doubled run count vs ( $K = 5$ )                                                        |
| Remarks                                  | Effective for small AF portfolio screening; easy to deploy and analyze. | Suitable for laboratory testing, allows additional AF interaction effects to be explored. | Study's whole two-level design combines statistical richness, coal savings, and experimental practicality. | Better statistically but impracticable for normal lab campaigns; high motivation for fractional designs. |

(about 41–42%), while still limiting the experiment to 32 runs, which remains feasible in terms of cost and lab laboratory effort (Fig. 2).



**Fig. 2.** Cost coal saving tradeoff for different  $K$  factorial design.

These results indicate that the LP solution tends to push AF levels toward their upper bounds. This behavior follows directly from the objective function, since increasing AF usage reduces the need for the more expensive Mixed Coal variable  $MC_j$

while still satisfying the linear NCV constraints.

### 3.2 AF mixture quantities and mixed coal requirements for the case study

Five Alternative Fuels (AFs) were selected as experimental factors because they satisfy the minimum  $NCV_{as-received}$  required for SLC operation. Their calorific values and unit costs differ: AF1 (4200 Mcal/ton, 1380 THB/kg), AF2 (3100 Mcal/ton, 1770 THB/kg), AF3 (4000 Mcal/ton, 1400 THB/kg), AF4 (2800 Mcal/ton, 1560 THB/kg), and AF5 (3800 Mcal/ton, 1695 THB/kg). Mixed Coal (MC), used only when AF energy is insufficient to reach the target of 150,000 Mcal/hr, has the highest calorific value (6100 Mcal/ton) and the highest cost (5200 THB/kg). These data define the economic and thermal conditions considered by the optimization model.

At laboratory scale, a minimum Low–High separation of 0.1 g was imposed for each AF to ensure statistically meaningful contrasts and practical weighing accuracy. The LP model determined Low–High ranges that satisfy two constraints: (i) total AF mass in each treatment does not exceed 18 g, and (ii) the combined AF energy allows MC addition to meet the SLC heat demand. All AFs converged to this minimum spacing, indicating that wider ranges would either increase cost or violate the mass–energy limits (Fig. 3).

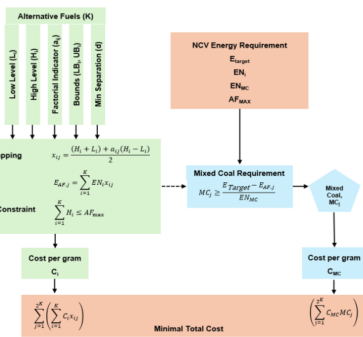


Fig. 3. Flowchart representing the model.

Using these optimized levels, a full  $2^5 = 32$  run two-level factorial design was generated. Each run represents one unique Low–High combination of AF1–AF5, ensuring orthogonality and balanced coverage of the experimental space. The AF mass in each treatment is obtained from the Low–High levels and the factorial indicator  $a_{ij}$  through the linear relation in Eq. (2.6), producing physically meaningful quantities that respect laboratory precision and the 18 g cap. Although all AFs share the same 0.1 g separation, their different  $NCV_{as-received}$  values lead to distinct total energy outputs across treatments.

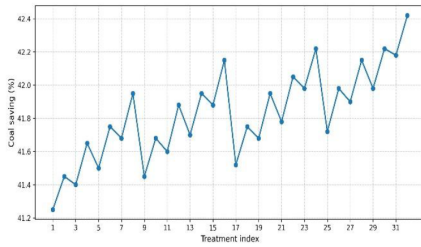
The  $NCV_{as-received}$  of each AF mixture is calculated using Eq. (2.8). Since individual AF values range from 2800 to 4200 Mcal/ton (plant data), some combinations

approach the thermal target more closely than others, even when total AF mass is similar. When the AF energy is insufficient, MC is added according to Eq. (2.7) to reach 150,000 Mcal/hr. Because MC has the highest  $NCV_{as-received}$ , small mass additions are sufficient, but its high unit cost strongly affects the total experimental cost.

Treatments rich in higher- $NCV_{as-received}$  AFs require the least MC, while those dominated by lower- $NCV$  fuels require more. This shows how small changes in AF allocation, driven by Low–High settings, directly influence energy balance and cost. The optimized solution yields Low–High levels of 3.9–4.0 g (AF1), 2.0–2.1 g (AF2), 0.9–1.0 g (AF3), 5.0–5.1 g (AF4), and 5.7–5.8 g (AF5), all within plant limits and satisfying the 0.1 g separation. Most AFs are pushed toward their upper bounds, reflecting the economic benefit of replacing expensive MC. Total AF mass in all 32 treatments remains between 17.5 and 17.9 g, below the 18 g limit, while MC requirements fall in a narrow range of about 14.2–14.5 g, compared with about 24.6 g for a pure-coal case.

Fig. 4 shows that coal savings for all treatments are consistently around 41–42% relative to the pure-coal baseline. Higher savings are associated with High levels of AF4 and AF5, which have favorable  $NCV$  and cost. The narrow spread of the curve indicates a robust operating window: moderate changes in AF levels within the optimized range do not cause large losses in coal savings, which is attractive for plant operation and emission reduction.

The total cost of performing the full 32-run design is 3,277,554.75 THB, with individual runs costing about 102,200–102,800 THB. This small variation reduces cost-related bias in later statisti-



**Fig. 4.** Coal saving (%) for the 32 AF factorial treatments relative to pure-coal operation at the same  $NCV_{as-received}$ .

cal analysis of process responses such as  $NCV_{as-received}$ , combustion stability, and emissions. Overall, the optimized factorial plan satisfies all mass and energy constraints, achieves stable coal substitution of more than 40%, and keeps experimental cost within a predictable range. Compared with non-optimized designs based on trial-and-error Low–High choices, the proposed framework provides a more consistent, economical, and operationally realistic basis for planning AF experiments and linking laboratory studies with practical SLC operation.

### 3.3 Scalability and practical limits of the $K$ -factor AF model

For a general case with  $K$  Alternative Fuels, the proposed model generates an economically optimized two-level factorial design that satisfies AF mass limits,  $NCV_{as-received}$  requirements, and the minimum Low–High separation. Each fuel  $AF_i$  is assigned a Low level  $L_i$  and a High level  $H_i$  ( $H_i - L_i \geq d$ ), and the factorial indicators  $a_{ij}$  map these levels to the AF masses  $x_{ij}$  in each of the  $2^K$  treatments. The LP objective then minimizes the total cost of AFs and Mixed Coal over all treatments, while ensuring that the total AF mass and the combined  $NCV_{as-received}$  meet the operational targets. This structure makes the framework directly scalable and suitable for

redesigning experimental plans under different fuel portfolios, cost data, or energy requirements.

When  $K$  becomes large or the separation  $d$  is chosen very small, the problem size increases rapidly. A small  $d$  implies fine resolution in AF dosing, leading to many similar Low–High combinations, while the full factorial structure causes the number of treatments and energy–cost evaluations to grow exponentially as  $2^K$ . Although such cases remain conceptually within the same LP structure, they can become computationally demanding and experimentally impractical. In these situations, fractional factorial or screening designs can be used to reduce the number of runs while preserving the main structure of the optimization model, as summarized in Table 3.

From a practical viewpoint, a full  $2^K$  design is also limited by laboratory and operational constraints. Increasing  $K$  from 5 to 8, for example, raises the number of experiments from 32 to 256, which is rarely feasible in terms of time, cost, and material handling. Each run requires controlled preparation of AF mixtures, stable SLC-like conditions, and detailed measurements of  $NCV_{as-received}$ , emissions, and ash properties. As  $K$  grows, maintaining consistency across all treatments and justifying the overall experimental cost become increasingly difficult. Therefore, the proposed framework is most effective for moderate  $K$  and should be combined with factor screening or reduced designs for larger AF portfolios.

Metaheuristic methods, such as Genetic Algorithms, Particle Swarm Optimization, Differential Evolution, and recent swarm-based techniques, could also be applied to explore large- $K$  cases without enumerating all  $2^K$  combinations. These approaches can search high-dimensional spaces efficiently, but they require exten-

**Table 3.** Summary of Main Findings, Advantages, and Limitations of the Proposed AF Experimental Planning Framework.

| Aspect                                           | Main findings<br>(general $K$ -factor case)                                                                                                                                                                 | Advantages                                                                                                                                                                                     | Limitations                                                                                                                                                                                                                       |
|--------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Feasibility of AF factorial design               | A two-level factorial design is created, employing optimum Low-High levels for ( $K$ ) AFs and limiting overall AF mass to the stated loading limit.                                                        | Makes all treatments experimentally possible and compliant with SLC feeding limits; retains orthogonal factorial structure for statistical analysis.                                           | Increasing the number of runs exponentially with $K$ may be impractical for big ( $K$ ), requiring re-optimization for various plants or investments.                                                                             |
| NCV <sub>as-received</sub> and coal substitution | The combined NCV <sub>as-received</sub> from AFs and Mixed Coal (MC) achieves the goal value for all treatments. AFs partially replace coal, while MC serves as a balancing fuel.                           | Allows systematic coal substitution scenario evaluation while meeting combustion energy requirements; aids decarbonization and fossil-fuel reduction.                                          | This framework quantifies coal savings under model assumptions and laboratory-scale settings, not full-scale kiln validation or dynamic impacts.                                                                                  |
| Experimental cost profile                        | The total cost of executing all ( $2^K$ ) treatments is computed by aggregating AF and MC costs; the optimization constrains the design to a relatively narrow cost band per treatment.                     | Provides a clear budget estimate for the entire experimental campaign; limited cost variation reduces economic confounding in the interpretation of process responses.                         | Cost parameters (AF and coal prices, handling, etc.) are plant- and time-specific; re-estimation is needed when price structures or logistics change.                                                                             |
| Economic and operational robustness              | Within the optimized Low-High ranges, coal savings and cost remain stable across all ( $2^K$ ) combinations of AF levels; the coal-savings curve is smooth and tightly clustered.                           | Indicates a robust operating window: moderate deviations in AF dosing around the optimized ranges still preserve substantial coal savings and cost efficiency.                                 | Robustness is assessed only inside the optimized design region; extreme operating conditions, AF quality variability, or equipment constraints beyond the model are not explicitly represented.                                   |
| Role of individual AFs (factors)                 | The framework can identify which AFs (factors) exert the strongest influence on cost and coal savings through main and interaction effects in the factorial structure.                                      | Helps prioritize AF streams for procurement, quality control, and further process studies; guides which factors are most critical to maintain within tight bounds.                             | The relative importance of factors depends on their specific NCV <sub>as-received</sub> cost, and bounds; changes in data or adding/removing AFs may alter factor rankings.                                                       |
| Methodological contribution                      | The study integrates a linear optimization model with a two-level factorial design for ( $K$ ) factors to generate an AF experimental plan that is simultaneously feasible, coal-efficient, and cost-aware. | Provides a general decision-support framework that can be applied to different numbers and types of AFs, enabling pre-experimental screening and avoidance of economically suboptimal designs. | The current formulation focuses on full ( $2^K$ ) designs and a single primary target (NCV <sub>as-received</sub> ); extension to fractional designs, very large ( $K$ ), or multi-response optimization is left for future work. |

sive parameter tuning and computational expertise, which may limit their acceptance in routine industrial practice. In contrast, the LP-based factorial framework is transparent, easy to verify, and compatible with standard engineering tools, making it more suitable for regular planning tasks when  $K$  kept within a manageable range.

Finally, the same linear optimization structure can be coupled with other experimental designs, such as Taguchi arrays, fractional factorials, or screening designs. In these cases, the AF mass

and NCV<sub>as-received</sub> constraints remain unchanged, but the number of design points is reduced and the objective is redefined over the selected subset of treatments. This flexibility allows the proposed model to function as a general economic planning layer that can support different design-of-experiments strategies while maintaining realistic energy and cost considerations.

#### 4. Conclusion

This paper presents an integrated mathematical framework that combines a

two-level complete factorial design with a Linear Programming (LP) formulation to support cost-effective planning of Alternative Fuel (AF) experiments for a simulated SLC process in the cement industry. By embedding optimal Low–High AF usage levels within the factorial structure, the model enables prior calculation of AF mass compositions, calorific contributions, and Mixed Coal supplementation for all  $2^K$  experimental runs before laboratory testing begins. This approach addresses a major gap in existing AF studies, which usually emphasize combustion performance and emissions while rarely considering experimental cost, material consumption, and practical feasibility at the laboratory scale.

The results show that the LP-embedded factorial model successfully identifies feasible Low–High AF ranges that satisfy both laboratory mass limits and SLC energy requirements. Although the optimization yields a small minimum separation of 0.1 g between Low and High levels, the complete factorial design still spans the full design space, covering all 32 Low–High combinations for the five selected AFs. Clear trends are observed in the energy and cost balances: high-NCV AFs (e.g., AF1 and AF3) significantly reduce the need for Mixed Coal and thus lower total cost, whereas low-NCV fuels (particularly AF4) increase dependence on expensive coal supplementation. These findings indicate that cost sensitivity is governed primarily by calorific performance rather than by unit fuel price alone.

The economic evaluation across all factorial treatments reveals substantial variation in total experimental cost, highlighting the importance of systematic pre-experimental planning. The proposed framework therefore functions as a quan-

titative decision-support tool, allowing cement plants to assess the full financial implications of laboratory campaigns, identify cost-effective AF combinations, and prioritize fuels that deliver the greatest energy substitution benefit. This supports more efficient resource allocation, reduces procurement waste, and strengthens the linkage between laboratory-scale design and industrial SLC operation.

Compared with heuristic or non-optimized planning, the proposed approach ensures compliance with energy constraints through explicit Mixed Coal balancing, avoids impractical AF combinations, preserves full factorial orthogonality without unnecessary trials, and markedly reduces the risk of excessive experimental expenditure. By integrating economic optimization with statistically rigorous design of experiments, the framework enhances both the analytical quality and the cost efficiency of AF research.

Overall, this study demonstrates that coupling factorial design with linear optimization provides a robust and flexible planning tool for alternative fuel experimentation. The method is scalable to any number of AF variables, adaptable to different calorific and cost datasets, and applicable to a wide range of industrial combustion systems beyond the cement sector. Future developments may incorporate non-linear combustion behavior, emissions constraints, moisture-corrected NCV, or air–fuel variability; nevertheless, the present model already establishes a strong foundation for more systematic, data-driven, and economically sustainable AF experimentation.

## **Acknowledgments**

This work was supported by the research funding from the Faculty of En-

gineering, Thammasat School of Engineering, and by the Applied Optimization Research Unit, Faculty of Engineering Sriracha, Kasetsart University, Sriracha Campus. Authors wish to thank N. Pokkrong, W. Sukanthmala and T. Khamwongkhong on the early phase of this study.

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