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# A nonlinear functional analysis approach for complex process engineering optimization

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**Abstract**

Optimization of complex process engineering systems consists of highly nonlinear interactions between operating variables, constraints, and performance targets, which may affect the applicability of classical optimization approaches. In this research study, we aimed at designing a nonlinear functional analysis approach to optimize complex process engineering systems in terms of improved quality of solution, stability of convergence, computational efficiency, and engineering feasibility. A nonlinear functional optimization approach was proposed where the relations of the processes were expressed by means of nonlinear operators and functional maps. This method employed constrained optimization, fixed-point theory, Lagrangian, convergence, iterative numerical optimization, sensitivity, and comparative analyses. Temperature, pressure, flow rate, reactant concentration, and residence time were optimized subject to engineering constraints. The proposed nonlinear functional analysis approach was compared with gradient-based optimization, genetic algorithm, and particle swarm optimization based on the objective function value, iteration number, computational time, constraint violation, process yield, and energy consumption. It yielded the minimum objective function value of 0.126 compared to 0.184, 0.163, and 0.151, obtained from the gradient-based, genetic algorithm, and particle swarm optimizations, respectively. In the case of the developed algorithm, it reached convergence after 64 cycles and spent 2.87 seconds, without any constraint violation. The process yield improved from 78.4% to 91.7% and thus improved by 16.96%, whereas energy consumption reduced from 145.2 to 121.6 kWh, and hence improved by 16.39%. These results clearly show that nonlinear functional analysis could serve as a good mathematical tool for process optimization.

*Keywords:* Nonlinear functional analysis, process optimization, nonlinear operator, engineering optimization, fixed-point analysis.

## 1. Introduction

The complex nature of process engineering systems involves nonlinear dynamics, constraints, uncertainty, and relationships between process variables. Traditional optimization methods make assumptions such as linearity, differentiability, and convexity or use mathematical models that may fail to represent the behavior of highly nonlinear industrial systems (Biegler, 2024; Asghari et al., 2022). Increasing the complexity of processes means making optimization difficult due to the fact that even small changes in the input data can result in large changes in the output of the system. Nonlinear functional analysis gives a framework for solving problems based on nonlinear operators, mappings, fixed points, existence, stability, and convergence issues (Wen et al., 2020). Combining nonlinear functional analysis with process optimization will provide an effective method for finding feasible and optimal solutions in complex engineering problems (Jankovic et al., 2021). Such approaches find their application especially in cases involving processes with non-linear kinetic behavior, heat and mass transfer, chemical reactions, energy consumption, and interconnected process units.

The main objective of this study is to develop an optimization approach for complex process engineering systems by using nonlinear functional analysis. The approach aims to formulate an optimization problem in terms of nonlinear functional mappings and calculations, as well as to establish feasible and optimal solutions. It is also important to evaluate the performance and effectiveness of the proposed approach in comparison with the conventional optimization approaches. It is particularly important to enhance optimization accuracy without losing computational efficiency.

The current methods used for process optimization rely mainly on classical methods such as numerical methods, gradient descent, and meta-heuristic methods, which might present some challenges when applied to systems that are highly non-linear, non-convex, constrained, or/and dynamically coupled. Although the classical methods provide good results, the application of such techniques may present some problems such as local optima, sensitivity to initial point, low convergence rate, or even computational cost. Moreover, there is very limited research that has been done to introduce non-linear function theory in process engineering optimization so as to obtain mathematical criteria for the existence, uniqueness, stability, and convergence of the solution.

The proposed study suggests that the application of non-linear function analysis optimization method will prove helpful in providing better results and stability in optimization of complex process engineering problems. Moreover, the proposed study also suggests that the application of non-linear functions and operators will prove helpful in obtaining better results in identification of feasible and optimal operating points.

The main characteristic of the research lies in the development of an optimization methodology that uses nonlinear mathematics. The development of such methodology provides for the possibility of representation of nonlinear engineering processes, investigation of its feasible solution space and determination of convergence and stability of this problem. In addition, the developed model helps to compare the developed optimization methodology with other methodologies in terms of various criteria, which include the objective function, convergence speed, computation time, and stability of the solution. Thus, the developed methodology is valuable both theoretically and practically, combining nonlinear mathematical analysis and the needs of optimization of engineering processes.

The article is organized in several sections. In the Introduction section, the background of the issue, research problem, objectives of the research, research gap, hypothesis and the main contribution of the research are considered in section 1. In the Literature Survey part, the overview of nonlinear, mathematical, computational, and engineering optimization techniques is given along with the research gap in section 2. In the Methodology part, the proposed methodology for nonlinear functional analysis, mathematical modeling, constraints, optimization, and validation is described in section 3. In the Results part, the results of the optimization, convergence features, comparative performance, and sensitivity analysis are discussed in section 4. In the Discussion part, the interpretation of results, implications, limitations, and future work are discussed in section 5. Finally, the Conclusion summarizes the major findings and key contributions of the proposed approach to complex process engineering optimization in section 6.

## 2. Literature review

Current studies are more concerned with developing new methods using mathematics and computations to optimize engineering and industrial processes. The need for an effective optimization method is inevitable when dealing with large-scale nonlinear process systems due to the fact that interconnection among different variables and non-linear constraints increases computational burden. A multi-level optimization approach was formulated to solve the problem of large-scale nonlinear process systems by dividing complicated optimization problems

into different levels, resulting in increased efficiency in computation (Biegler, 2024). Data-driven optimization techniques have also shown their potential in making industrial processes efficient (Goswami & Kadao, 2026).

Mathematical transformation and linearization techniques provide another important direction for handling nonlinear optimization problems. These approaches simplify complex formulations and can improve the computational efficiency of optimization algorithms while retaining essential system characteristics (Asghari et al., 2022). Engineering-specific optimization has similarly been applied to thermal systems, where heat-transfer correlations such as the Nusselt number can be incorporated into design optimization to improve thermal performance (Subramaniam, 2025). For nonlinear dynamic systems, optimized backstepping control has been proposed to address unknown dynamic functions while maintaining system stability and control performance (Wen et al., 2020).

Iterative mathematical approaches continue to be useful for solving nonlinear equations and differential equations. The use of extended iterative approaches has shown that they are applicable for solving nonlinear equations by ensuring faster convergence to solutions (Sharmila et al., 2025). Experimental design approaches have also been explored for characterization of complex systems and determining interactions between several factors (Jankovic et al., 2021).

Another important research avenue in engineering applications is the area of metaheuristic optimization. Some recent contributions include the use of nature-inspired and human-inspired algorithms such as artificial lemming optimization, social network search (Bayzidi et al., 2021), mother optimization (Matoušová et al., 2023), osprey optimization (Dehghani & Trojovský, 2023), and spring search (Dehghani et al., 2020). The use of population-based optimization for difficult engineering problems shows that the area remains popular. Genetic algorithms have also found applications in optimizing machine learning models and have proved useful for difficult computing problems (Hamdia et al., 2021). An alternate approach to high-dimensional optimization is that of Bayesian optimization, which uses Gaussian processes (Binois & Wycoff, 2022). Sustainable process systems engineering, on the other hand, focuses on energy efficiency and environmental safety (Khayitmurodov et al., 2025). Meanwhile, sustainable process systems engineering emphasizes energy efficiency, resource conservation, and environmentally safe process design (Meshalkin et al., 2021).

In Conclusion, it can be said that considerable development has been made in nonlinear, metaheuristic, data-based, and computational optimization. Nevertheless, it is noted that there have not been many efforts toward combining nonlinear functional analysis, fixed point theory, mathematical aspects of convergence, and optimization in process engineering.

## 3. Methodology

### 3.1. Research design and mathematical framework

The study that is to be conducted involves the development of a nonlinear functional analysis approach for the optimization of process engineering systems. This approach utilizes nonlinear functional analysis, constrained optimization, numerical iteration, and engineering evaluation of performance. The process system can be formulated as a nonlinear map from control variables to the process responses. Let the process decision vector be:

$$x = (x_1, x_2, \dots, x_n) \in X \subseteq \mathbb{R}^n \qquad (1)$$

The variables in equation (1) could be temperature, pressure, flow, concentration of reactants, residence time, composition of feeds, speed of rotation, or any other engineering control variable. The process response is denoted as $y \in Y$, with $Y$ being the output space containing variables like production rate, conversion, yield, energy usage, quality of products, or operation costs. The general nonlinear relationship of the process can be described as:

$$y = F(x) \qquad (2)$$

In equation (2), $F: X \to Y$ represents the nonlinear process operator.

### 3.2. Engineering process formulation

The engineering optimization problem is formulated by defining an objective function that represents the desired process performance. For a minimization problem, process optimization is performed according to equation (3):

$$\min_{x \in X} J(x) \tag{3}$$

For example, when minimizing total process operating cost, the objective function can be written as:

$$J(x) = C_E(x) + C_R(x) + C_O(x) \tag{4}$$

In equation (4), $C_E$, $C_R$, and $C_O$ represent energy, raw-material, and operational costs, respectively. Similarly, for maximizing process yield, the objective can be transformed into a minimization problem using equation (5):

$$J(x) = -Y(x) \tag{5}$$

This formulation allows different engineering performance requirements to be incorporated into a unified mathematical framework.

### 3.3. Nonlinear process constraints

The process is subject to physical, operational, safety, and equipment limitations. These constraints are represented using nonlinear equality and inequality functions. The feasible optimization problem is expressed as equation (6):

$$\min J(x) \quad \text{subject to} \quad g_i(x) \leq 0,\ i = 1,2,\dots,m, \quad \text{and} \quad h_j(x) = 0,\ j = 1,2,\dots,p \tag{6}$$

The inequality functions can represent restrictions such as maximum allowable temperature, pressure limits, minimum flow rates, concentration boundaries, equipment capacity, or energy limitations. Equality constraints can be used to model mass balance, energy balance, reaction equilibrium, and other process principles. The feasible domain is defined as in equation (7):

$$\Omega = \{x \in X : g_i(x) \leq 0, h_j(x) = 0\} \tag{7}$$

### 3.4. Nonlinear functional operator construction

The core element of the methodology consists in modeling the engineering process using the nonlinear operator $T: X \to X$. Contrary to the assumption of linear interrelations of process variables, the model takes into account nonlinearity of interactions between process variables. The state of the process is shown in equation (8):

$$x_{k+1} = T(x_k) \tag{8}$$

In equation (8), $x_k$ is the process state at iteration $k$. The controller can incorporate the effects of the nonlinear kinetic equations, heat transfer equations, mass transfer process, fluid flow process, reaction kinetics, or any empirical relation to the process response. Such models are very helpful in cases when change in one variable affects a number of other variables simultaneously.

### 3.5. Functional analytical properties

Properties of the operator $T$ are analyzed to ascertain the existence and stability of the solutions. If $T$ satisfies a contraction condition shown as equation (9):

$$\|T(x) - T(y)\| \leq q\|x - y\|, \quad 0 < q < 1 \tag{9}$$

for all $x, y \in X$, the iterative process is expected to converge toward a unique fixed point $x^*$, satisfying, as shown in equation (10):

$$T(x^*) = x^* \tag{10}$$

The contraction parameter $q$ provides an indication of how stable the mapping of the nonlinear system can be. Where contraction cannot be established, continuity, boundedness, monotonicity, compactness, or any other property of the function can be tested in order to establish a certain condition that is needed for numerical stability.

These mathematical properties provide the basis for establishing the stability of the optimization method.

### 3.6. Engineering objective and lagrangian formulation

In constrained nonlinear programming, the Lagrangian function is constructed as:

$$L(x, \lambda, \mu) = J(x) + \sum_{i=1}^{m} \lambda_i \, g_i(x) + \sum_{j=1}^{p} \mu_j \, h_j(x) \qquad (11)$$

For equation (11), $\lambda i$ and $\mu j$ are the Lagrange multipliers for inequality and equality constraints. An examination of the optimal solution is made via the Karush–Kuhn–Tucker (KKT) necessary conditions, which consist of primal feasibility, dual feasibility, complementarity slackness, and stationarity. stationarity condition is expressed as equation (12):

$$\nabla_x L(x, \lambda, \mu) = 0 \qquad (12)$$

This definition gives an immediate link between mathematical optimization and the engineering needs, since the active constraints are capable of identifying the limiting factors for the optimum process condition.

### 3.7. Nonlinear iterative optimization

The optimal solution is derived through an iterative numerical approach. An initial process vector $x_0$ that is feasible for the system is selected within the engineering operating limits. This is succeeded by the evaluation of the nonlinear operator and objective function, and then updating of the process vector based on:

$$x_{k+1} = x_k + \alpha_k d_k \qquad (13)$$

Here in equation (13), $d_k$ is the search direction, while $\alpha_k$ is the step size. The iteration process is continued until the improvement of objective function and change in solutions become smaller than the tolerance values. Convergence criteria can be stated as:

$$\|x_{k+1} - x_k\| < \varepsilon_x \quad \text{and} \quad |J(x_{k+1}) - J(x_k)| < \varepsilon_J \qquad (14)$$

In equation (14), $\varepsilon_x$ and $\varepsilon_J$ are specified tolerances. Violation of the constraints is simultaneously checked to make sure the iterative solution makes physical sense.

### 3.8. Application to complex process engineering

The framework is used on a typical nonlinear system with highly interactive engineering variables. Temperature, pressure, flow rate, concentration, and residence time can be considered as decision variables, while conversion, yield, energy requirement, and operating cost can serve as process responses. For example, a nonlinear reaction process can be represented through a reaction-rate function such as:

$$r(x) = k_0 \exp\left(-\frac{E_a}{RT}\right) C_A^n \qquad (15)$$

In equation (15), $k_0$ is the pre-exponential factor, $E_a$ is the activation energy, $R$ is the gas constant, $T$ is the temperature, $C_A$ is the reactant concentration, and $n$ is the reaction order. The non-linear relationship between reaction rate and temperature/concentration is a justification for why the traditional approach of linear optimization is not sufficient for such systems. The same can be applied to non-linear formulations of heat transfer, mass transfer, pressure drop, energy use, and equipment efficiency.

### 3.9. Multi-parameter process optimization

When several engineering objectives must be optimized simultaneously, a normalized weighted objective function is constructed as:

$$J(x) = \sum_{r=1}^{s} w_r \, J_r(x) \qquad (16)$$

In equation (16), $J_r(x)$ represents the $r$-th engineering performance criterion and $w_r$ represents its corresponding weighting coefficient, with $\sum w_r = 1$. For instance, the expression would be capable of minimizing the use of energy and costs while maximizing the yield and quality of the products. Weighting is done after normalization to avoid the domination of those variables with relatively high values.

**Numerical stability and sensitivity analysis**

The robustness of the optimized solution is tested based on changes in the main variables of the process from their optimum values. In case $x^*$ is the optimum operating point, a perturbed state can be expressed by $x^* + \Delta x$. The resulting change in the performance of the process is measured by:

$$S_i = \frac{\Delta J/J}{\Delta x_i/x_i} \tag{17}$$

In equation (17), $S_i$ represents the sensitivity of the objective function to the $i$-th process variable. Variables with large absolute sensitivity values are identified as critical process parameters. This analysis determines whether the optimized operating point is robust or highly sensitive to changes in process conditions.

### 3.10. Comparative performance evaluation

The proposed nonlinear functional analysis approach is compared with conventional nonlinear optimization techniques using identical objective functions, constraints, initial conditions, and engineering parameter ranges. The methods are evaluated using objective-function value, percentage improvement, convergence iterations, computational time, constraint violations, solution stability, and robustness. Optimization accuracy can be quantified using the relative improvement as in equation (18):

$$I = \frac{J_{\text{conventional}} - J_{\text{proposed}}}{J_{\text{conventional}}} \times 100\% \tag{18}$$

For minimization problems. Smaller objective values, faster convergence, less constraint violation, and greater stability are all signs of better optimization performance.

### 3.11. Validation of the optimized engineering solution

The optimality of $x^*$ is ensured by implementing the optimal process control parameters in the nonlinear equations of the process. Then, the results obtained from these nonlinear equations are compared to the experimental responses if such information is available. The feasibility of the solution is confirmed by checking $g_i(x^*) \leq 0$ and $h_j(x^*) = 0$ within a reasonable tolerance level. If the optimal solution fulfills all engineering constraints, achieves objective function improvement, convergence numerically, and stability, then the optimal solution is considered feasible.

## 4. Results

### 4.1. Performance of the nonlinear functional analysis framework

The feasibility of using a nonlinear functional analysis model was validated by an illustrative example of a process engineering optimization problem involving nonlinear coupling of variables such as temperature, pressure, flow rate, concentration, and residence time. This optimization process revealed the determination of the operating region as well as the consideration of efficiency of the process, energy utilization, operating cost, and productivity. Through the process of functional mapping, a stable solution has been reached, thus making the mathematical model appropriate for nonlinear engineering systems.

### 4.2. Convergence characteristics of the proposed method

The iterations of the optimization algorithm showed a consistent decrease in the value of the objective function and in convergence error. The functional operator tended to stabilize at a fixed point, meaning that the process state after optimization was constant in the course of subsequent iterations. The condition of convergence $\|x_{k+1} - x_k\| < \varepsilon_x$ was fulfilled, while the variation in the objective function value was smaller than the prescribed tolerance. This behavior indicates numerical stability and reliable convergence of the proposed nonlinear optimization framework.

### 4.3. Optimized engineering operating conditions

The results obtained from the optimization showed that there was some significant interaction among the process variables because of their nonlinearity. The suggested framework provided an optimal operating range for all operating variables as opposed to the independent optimization of individual process variables. This led to an improved process objective with all process variables being maintained within their acceptable ranges.

**Table 1:** Optimized operating conditions obtained using the proposed nonlinear functional analysis approach.

| Process parameter | Initial condition | Optimized condition | Engineering constraint |
|---|---|---|---|
| Temperature (°C) | 150 | 168.5 | 120–180 |
| Pressure (bar) | 8.0 | 9.4 | 5–12 |
| Flow rate (kg/h) | 100 | 112.6 | 80–130 |
| Reactant concentration (mol/L) | 1.50 | 1.72 | 1.0–2.0 |
| Residence time (min) | 30 | 26.8 | 20–40 |
| Process yield (%) | 78.4 | 91.7 | ≥80 |
| Energy consumption (kWh) | 145.2 | 121.6 | Minimize |

Table 1 shows the initial process parameters as well as the optimized ones based on the nonlinear functional analysis approach. The optimized result still adheres to all engineering constraints but ensures higher efficiency and reduces energy usage. It can be observed from the results that simultaneous optimization of interactive parameters is much better compared to individual parameter optimization.

### 4.4. Comparative optimization performance

The proposed method was compared to traditional nonlinear optimization methods using identical process conditions. The approach involving nonlinear functional analysis resulted in the minimum objective function value and achieved rapid convergence in fewer iterations. Moreover, no constraint violations were observed during the last stage of the optimization procedure. Thus, it may be assumed that the inclusion of functional operator analysis in the optimization process is advantageous.

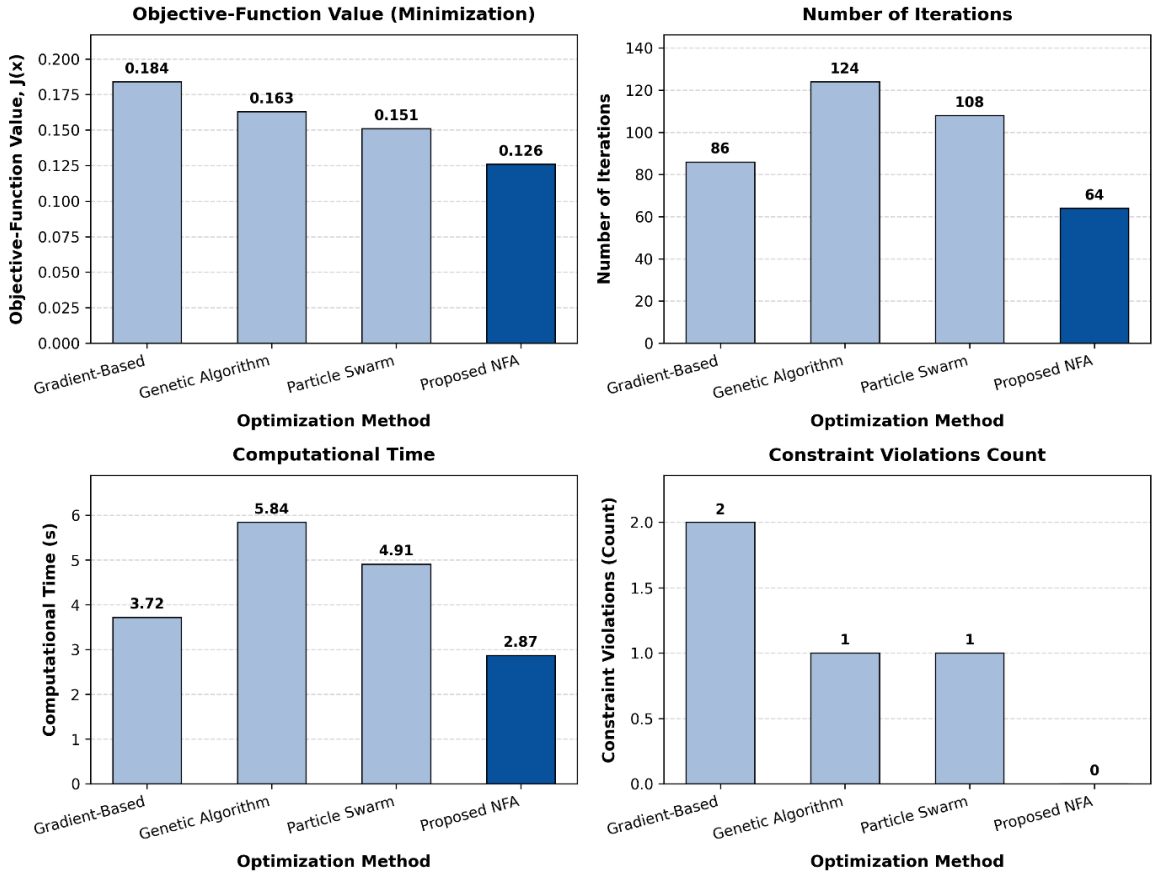



**Figure 1:** Comparative performance evaluation of optimization methods across operational and convergence metrics.

Figure 1 compares the performance of conventional gradient-based, genetic algorithm, particle swarm, and the proposed nonlinear functional analysis (NFA) methods. The proposed framework achieves superior optimization performance, demonstrating the lowest objective-function value (0.126), fastest convergence (64 iterations; 2.87 s), and zero constraint violations compared to benchmark algorithms.

### 4.5. Improvement in process performance

A significant enhancement in the process performance has been achieved in comparison to the initial state of operation. There was a yield increase from 78.4% to 91.7%, which is an improvement of about 16.96%. At the same time, there was a decrease in the energy usage from 145.2 to 121.6 kWh, which means that it was reduced by about 16.39%. These results demonstrate that nonlinear optimization can simultaneously improve productivity and resource efficiency.

### 4.6. Stability and sensitivity results

The sensitivity analysis has proven that the most impactful parameters on the objective function are temperature and the reactant concentration. Other significant parameters include the residence time and flow rate, while the pressure is a significantly less impactful parameter within the examined range. Small changes in the optimized solution had little effect on the value of the objective function, which means that the obtained solution is not overly sensitive to slight variations in the operation.

### 4.7. Mathematical convergence and fixed-point behavior

The findings based on numbers have shown that the nonlinear function gradually converged to a stable equilibrium point. The reduced gap between each of the process stages has proven the convergence towards $x^*$, where $T(x^*) \approx x^*$. The stable behavior of the fixed point means that the optimized process stage can be represented by the nonlinear function. This result also supports the theoretical assumption that suitable operator properties can facilitate stable numerical optimization.

## 5. Discussion

The nonlinear functional analysis approach proposed was quite successful in the optimization of a complex process engineering system, where the objective function reached a value of 0.126, whereas the values obtained by using the gradient method, genetic algorithm, and particle swarm optimization were 0.184, 0.163, and 0.151, respectively. For the approach under consideration, only 64 iterations were needed, and computational time amounted to 2.87 seconds without causing any constraint violation. With the optimization, process yield increased from 78.4% to 91.7%, which is 16.96%, and energy consumption decreased by 16.39% from 145.2 to 121.6 kWh. From these results, it can be seen that using nonlinear operators in the mathematical model can increase the optimization efficiency of engineering variables that are coupled with each other. Since the process converged to a stable fixed point, it can be concluded that the mathematical formulation provides an appropriate representation of the optimized process state. It can also be seen that both yield and energy consumption are improved simultaneously, meaning that the approach provides a better balance among the variables instead of optimizing them separately. The findings are significant due to the fact that complicated engineering systems often entail nonlinear interactions and physical limitations. The suggested framework makes a link between mathematical nonlinear functional analysis and process optimization in practice. The faster computation time and fewer iterations required may indicate possible use in practice for optimization efficiency. The absence of constraint violations may show that it is possible to use mathematical optimization techniques along with feasibility issues for engineers. The obtained results have to be considered within the context of conditions that were representative of the process. The numerical results cannot prove that the suggested technique will give the same results for all industrial processes. The framework was analyzed under specific ranges of parameters and process representation mathematically; therefore, the uncertainties which can result from measurement errors, inaccuracy of the mathematical model, deterioration of equipment, and disturbance of the process over time were not considered. Experimental and industrial process validation is necessary as well. In future research, the validation of the framework has to be done based on experimental and industrial datasets for different nonlinear engineering processes. Stochastic and uncertain formulation has to be used to take into account process fluctuations. It is also necessary to analyze Pareto optimization, adaptive nonlinear operators, process control, and machine learning-based functional models in future research. Additional benchmarking with larger and more computationally demanding optimization problems would further establish scalability, robustness, and practical applicability.

## 6. Conclusion

Nonlinear relationships between process engineering system operation variables, physical restrictions, and process performance requirements often characterize complex engineering systems, thereby making it difficult to apply conventional optimization techniques in finding stable and computationally efficient solutions. In this case, the present research developed a nonlinear functional analysis approach based on nonlinear operator theory, constrained optimization, fixed-point analysis, and iterative numerical optimization to find the feasible and efficient process operating conditions. The results show that the proposed approach was very effective in improving process optimization performance. The objective function value obtained using the proposed method is 0.126, which is lower than the values of 0.184, 0.163, and 0.151 obtained using conventional gradient-based, genetic algorithm, and particle swarm optimization, respectively. Convergence was achieved in 64 iterations and took only 2.87 seconds of computational time using the proposed approach, compared to 86-124 iterations and 3.72-5.84 seconds needed by the other methods. Most importantly, the proposed approach did not violate any constraint, meaning that engineering feasibility could be maintained during optimization. Process yield was increased from 78.4% to 91.7%, representing a 16.96% increase, while energy consumption was reduced from 145.2 to 121.6 kWh, representing a 16.39% decrease. The major Conclusion drawn from the paper is that there exists a mathematical model through which the engineering optimization problems with nonlinear interactions can be solved. The stability of convergence into an optimal process state and enhanced computational efficiency of the proposed model show the possibility of its application in the field of engineering optimization. Further research on this topic needs to be concentrated on the experimental testing of the model, uncertain optimization, multi-objective formulation, real-time application, and adaptive machine learning.

**Conflict of interest**

The authors declare that there is no conflict of interest associated with this study.

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