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Using Optimization Techniques Application in Solving Smart Manufacturing Problems

C. A. Udemba[1], E. Boldsaikhan[1], and J. P. Purswell[2]

[1] Department of Industrial, System, & Manufacturing Engineering
Wichita State University-Kansas
1845 Fairmount St, Wichita, KS 67260, USA

[2]Department of Engineering
Colorado State University, Pueblo
2200 Bonforte Blvd. Pueblo, CO 81001, USA

Corresponding author's Email: caudemba@shockers.wichita.edu

Author Note: Udemba Chiemezie Anthony is a Ph.D. student and Dr. Enkhsaikhan Boldsaikhan is an assistant Professor both at Wichita State University, Wichita, Kansas, and Professor J.P. Purswell is an adjunct professor at Colorado State University-Pueblo, Colorado.

Abstract: This study provides a novel strategy for assisting optimization techniques, as well as showing how technological advancements can help to provide a new viewpoint on smart manufacturing (SM). Manufacturing is usually connected with the transformation of raw materials and component assembly into finished products. This paper provides an update to the production that uses optimized procedures and processes to achieve optimum yield in heuristics, global optimization, and discrete optimization methods. This approach applies with the combining of process and operation analysis, with the development of the analytic model, holds the potential to improve many aspects of manufacturing industries. This article reviews several aspects of the SM process and introduces its advantages. Optimizing the product design process has substantial impact on global productivity, with factories able to improve their efficiency ratings by utilizing the connections formed from each manufacturing phase and optimizing each for maximum efficiency. In this review article, several papers published in recent years were analyzed to better understand the several ways of applying the Bayesian approach in optimization. This approach is defined by fixing a prior distribution and minimizing the risk functions when developing scheduling solutions for manufacturing systems.

Keywords: Smart manufacturing, Global Optimization, Discrete Optimization, Heuristics, and Bayesian Approach

1. Introduction

Manufacturing processes and production networks have evolved dramatically in recent years because of advances in digital information technology and advanced smart manufacturing techniques. As a result of these developments, estimating the economic, social, and environmental consequences of smart manufacturing activities has become increasingly important (Krishnamoorthy, Brodsky, & Menascé, 2014). The goal of this work is to provide a systematic methodology that quantifies overall smart manufacturing processes and describes numerous ways to use this approach in optimization, including global optimization, discrete optimization, heuristic, and Bayesian approaches (Andradóttir, 1996).

This study finds potential causes of the optimization techniques and evaluates the whole system using Bayesian optimization (BO) to better address these strategies in smart manufacturing problems. Bayesian optimization is a well-known strategy for resolving optimization problems with expensive objective functions. The authors (Snoek, Larochelle, & Adams, 2012; Lizotte 2008) critically reviewed BO as a robust analytical technique that is primarily used in the assessment of risk, reliability, and resilience of uncertainty. The model's quantification is investigated, and the findings are analyzed using several methods of sensitivity analysis and advanced optimization approaches. In such cases, BO approaches are extremely useful and construct a posterior distribution over the original expensive model using a computationally cheap surrogate model. There are two types of surrogate models used in BO: parametric and nonparametric regression models. Surrogate models with significant assumptions about the behavior of the objective function, such as nth-degree polynomials, are common (Snoek et al 2012).

Due to the sensitive nature of the systems, research on optimization strategies in SM has received little attention in recent years. The advantage of using the BO approach is the ability to include some expert knowledge when creating a prior distribution; while the disadvantage is the level of uncertainty when constructing a prior distribution on the set of problems to be optimized (Floudas & Pardalos, 2008). The researchers (Shao, Shin, & Jain 2014; Ren, Zhang, Liu, Sakao, Huisingh, & Almeida 2019) have seen a significant use of the BO in a variety of domains. In this research work, we studied a Gaussian process (GP) as a surrogate model, which has been trained to mimic the reaction of an expensive industrial product as the objective function. In the actual world, this is particularly restricted because the problem's complexity is frequently unknown. Surrogate models that are non-parametric do not make such assumptions, and the surrogate adjusts to new data. BO is a recent contribution to the structural optimization field and is widely employed by machine learning and artificial intelligence (Shao et al., 2014; Jamil et al 2013). To better understand SM techniques (Horst, Pardalos, & Van Thoai 2000), we must analyze and illustrate using the BO, the degree of confidence, and quantify inherent uncertainties of the manufacturing processes. To keep the manufacturing companies competitive and capitalizing on new opportunities, the development and implementation of a smart manufacturing assessment tool can help manufacturers prepare their operations for the challenges of today's technological advancements (Schonlau, Welch, & Jones, 1997).

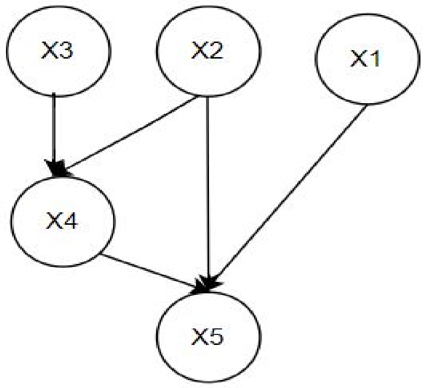
This study intends to promote a standard design or framework that can be used for both production and optimization techniques, allowing for more effort and innovation while also stimulating the acceptance and usage of smart manufacturing technology. In SM, optimizing the product design process has a substantial impact on global productivity, with factories being able to improve their efficiency ratings by utilizing the connections formed from each manufacturing phase and optimizing each for maximum efficiency (Kang, Lee, Choi, Kim, Park, Son, & Do 2016).

2. Methodology

Bayesian optimization (BO) is an optimization technique that simulates an expensive objective function using a stochastic surrogate model based on a finite number of function observations. The expensive objective function is assessed at the surrogate model's optimum at each iteration, and this new knowledge is used to retrain the surrogate (Schonlau, Welch, & Jones 1997; Vien, Zimmermann, & Toussaint, 2018).

The authors (Nannapaneni, Narayanan, Lechevalier, Sexton, Mahadevan, & Lee 2018) looked at how several forms of methodologies, such as analytical models, including neural networks (NNs), Gaussian process regression (GPR), decision trees, and Bayesian networks, have been developed and utilized to represent the data regarding Bayesian networks (BNs). This analysis is especially beneficial for smart manufacturing (SM) because of its capacity to accommodate diverse uncertainty sources and allow uncertainty quantification analysis. Several sorts of manufacturing process analytics are carried out, one of which is the introduction of smart manufacturing optimization strategies employing BNs. The authors also believed that having a common representation of such models is important to ease the implementation of BNs in manufacturing using several commercial tools. The widely utilized Gaussian process (GP) is used as a surrogate model in this study, and it has long been a key component of Bayesian approaches. To train the GP surrogate model, the BO technique requires an initial training set for smart manufacturing problems. In conducting our work, we examined the size and number of points in this training set and how they relate to the effect on the method's performance.

According to certain research (Ibne et al., 2020; Snoek et al 2008) the BNs aids in the prediction of interventions, the handling of missing data, and the avoidance of data overfitting. A variety of sophisticated analysis approaches, including heuristics, discrete optimization, and global optimization, among others, will be used to obtain additional understanding from the suggested model shown below. The background of the BN, which is a decision support tool commonly used in risk and resilience engineering, is provided in this section, with the three levels of specification used to represent the nodes interrelationships: root nodes, parent nodes, and child nodes. The root nodes' specification depicts the conditional interdependencies between nodes and edges, however, the conditional and joint probability distributions of the nodes are stated in an algebraic way by the parent nodes of specification, whereas the actual probability associated with a given node is determined by the child nodes (Ibne et al., 2020).



Root nodes: **X1, X2,** and **X3**

Non-root nodes: **X4, X5**

X4 is a child node with **X2** and **X3** as parent nodes

X4 and **X5** are child nodes associated with parent node **X2**

Figure 1. Systematic illustration of depiction of a Bayesian model with five variables

After training the parameters shown above, the uncertainties can be minimized using Bayesian inference, increasing the posterior probability. Bayesian inference can also be used to forecast machining process variables in a sequential probabilistic manner and the outcomes of the posterior knowledge, such as the first geometry, can be used as a prior for the analysis of the second geometry in posterior probability (Salehi, 2018). Bayesian inference is a knowledge-based method to current and future analysis that incorporates past information.

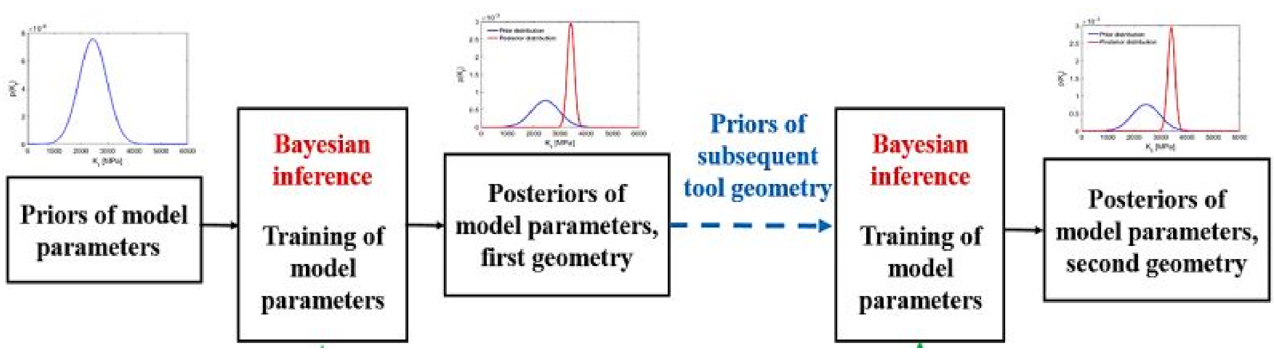


Figure 2. Predictive modeling for machining based on Bayesian statistics (Salehi, 2018)

3. Results

Despite the significant investment in a major approach, these authors (Shao et al., 2014; Shende et al., 2021) provided a comprehensive overview with two points and its stochastic, with three posterior samples with different length scale, with the same data and hyperparameter. This comprising is shown below:

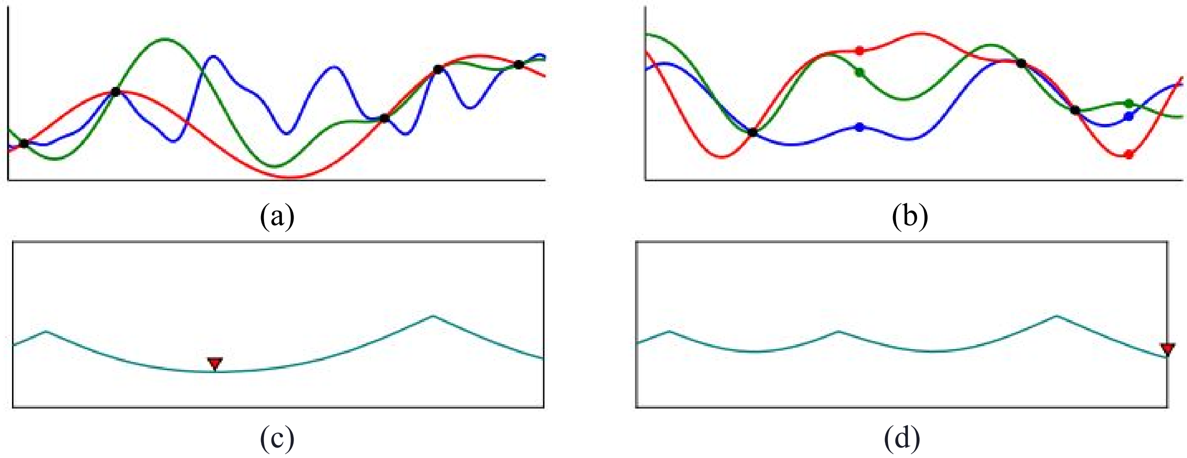


Figure 3. Illustration of Bayesian optimization a posterior sample under varying hyperparameter, b posterior samples after three data, c the GP surrogate model trained within two points, and d the expensive function is evaluated and added to the training data (Shao et al., 2014; Shende et al., 2021).

This paper contends that the objective can be met by allocating a strategy for each operation, such as the identification of common information that spans the product life cycle (U.S department of energy 2016; 2017; and 2018). The results show a proposed solution of the optimization techniques used in the Proton -exchange membrane (PEM) fuel cell in battery and vehicles. According to (Wipke, Sprik, Kurtz, Ramsden, Ainscough, & Saur 2012; Becker 1998) promoting and enforcing information representation standards define and demonstrate the architecture and technologies that support the system throughout its life cycle, as well as the mechanism that delivers feedback to the system. This will allow designers to create more effective products, processes, and systems in less time, as well as communicate more interactively, reducing faults and difficulties. The result of the proposed solution was considered. We studied and examined the following phase of the PEM fuel cells in Toyota automobiles for future development:

- Establish energy storage system targets for fuel cell hybrid automobiles, perform fuel cell hybrid vehicle system optimization, energy, storage, and vehicle system technical terms.
- Using the technical target tool, determine the sensitivity of fuel consumption to fuel technical targets applied across several vehicle platforms.
- Continue to test fuel cell vehicles for water and thermal management under real-world driving situations.
- Transfer a robust design technique to industry to overcome technical hurdles to fuel cell stack cost and durability.
- Determine how the technical targets tool may be used to anticipate national fuel consumption consequences. The initial sensitivity result utilizing the technical target tool, according to our study, reveals that the fuel cell system and motor efficiencies have a substantial impact on vehicle fuel economy.
- Based on our findings, we concluded that gasoline reformer warm-up could have a significant impact on fuel economy, and we set out to reduce this impact.

Several factors need to be considered when choosing a location for a facility as there are a few essential goals that must be met. The authors (Azkarate, Barthélémy, Hooker, Jordan, Keller, Markert, & Tchouvelev 2018) also demonstrated the advantages when choosing a location for a facility, however, a set of basic objectives must be followed as they are important to assure the facility's success. These objectives include but are not limited to:

- Skilled labor should be easily available near a facility's location
- Taxes, insurance, construction, and land prices must not be excessively “high”
- Utilities must be available quickly and at a “reasonable” cost
- It must be as close to raw material sources and customers as practicable
- Government rules at the local, state, and federal levels must be friendly to business

Toyota's motor production factory in Kentucky, Inc. 1010 Cherry Blossom Way, Georgetown, KY 40324, is its first location. An adequate supply of skilled labor in Georgetown, KY makes it a great site. According to data from the United States, the average employee’s median salary is $60,632, which is on the upper end of the pay scale for a manufacturing business in Georgetown. Toyota, on the other hand, offers a competitive wage for the surrounding area (U.S department of energy 2017). The second manufacturing facility is closer to Toyota's main hybrid buyer market; yet, it has a disadvantage for consumers and its second location will be Toyota motor manufacturing in Baja California. Essentially, the new facility will have a job shop space for customer requests, as well as product storage (Ronald M. Becker 2014).

4. Conclusion

In this paper, we have used the Bayesian approach in global optimization, discreet optimization, and heuristics with the objective of reducing the number of functions evaluations needed in SM techniques. Smart manufacturing is increasingly accepted and adopted by industry and academia; more fields and research areas have found potential in adapting smarter manufacturing standards to the larger systems. Many manufacturers are already taking advantage of the increasing capabilities of technologies such as energy management systems, advanced metering/sub-metering solutions, and internet-connected sensors. To solve this problem, we combined many steps utilizing various methods proposed in batch BO. Many public presentations and publication have been produced, without a conclusive result, that shows an effective method of transmitting information and design sensibilities to industries. Because of numerous advantages, such as high-power density, high energy conversion efficiency, fast start-up, low sensitivity to orientation, and environmental friendliness, proton exchange membrane (PEM) fuel cells, which directly convert chemical energy to electrical energy, have received a lot of attention in the battery industry. PEM cells are thought to be far from ideal and efficient, thus, there is potential for improvement; Otherwise, it would be a dying, inefficient technology. However, it is vital to understand the principles of PEM fuel cells, such as cell structure, thermodynamics, and the kinetics of fuel cell electrochemical reactions. The following is a summary of this research's contribution to the body of knowledge in SM:

- Advanced analysis should be performed to assess the efficiency of the suggested model and generate new ideas on how to improve the overall process in smart manufacturing
- Usage of BOs as an effective tool in solving optimization technique challenges in smart manufacturing - robustness is one of its primary advantages
- The Gaussian process (GP) surrogate model is effective for solving optimization techniques in SM problems
- Limiting the size of the training set is another way to improve BO's computational efficiency

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