

Adaptive Machine Learning Approach for Lean SAP Production Planning and Real-Time Inventory Optimization

Amir Hossein Rahimi

Iranian Institute of Machine Learning, Iran

Leila Farzan

Center for Intelligent Computing Research, Iran

ABSTRACT

Manufacturing organizations increasingly require production planning systems that can respond to demand variability, inventory uncertainty, process disturbances, and continuously changing operational conditions. Conventional SAP production planning approaches provide structured transaction and planning capabilities, but their effectiveness can be constrained when planning decisions depend on static parameters, manually adjusted forecasts, or optimization procedures that do not adequately adapt to changing data patterns. This research proposes an adaptive machine learning approach for lean SAP production planning and real-time inventory optimization. The proposed framework integrates stochastic approximation, adaptive optimization, non-convex learning, and convergence-oriented machine learning principles with SAP-oriented production and inventory decision processes. The methodological foundation is derived exclusively from the supplied literature on stochastic approximation, gradient-based optimization, implicit regularization, proximal algorithms, heavy-ball methods, and convergence behavior. The framework conceptualizes SAP planning as an adaptive decision problem in which demand signals, inventory states, production constraints, and replenishment requirements continuously update model parameters. A hybrid optimization architecture is proposed to balance responsiveness, computational stability, inventory reduction, and production throughput. The analysis indicates that adaptive learning can strengthen lean planning by reducing dependence on fixed planning assumptions while maintaining controlled optimization behavior. The study further identifies the importance of convergence conditions, learning-rate management, stochastic variability, and model stability for operational deployment. The proposed framework provides a theoretically grounded foundation for integrating adaptive machine learning into SAP production planning and real-time inventory management while recognizing limitations associated with data quality, non-convex optimization, computational requirements, and operational constraints.

KEYWORDS: Adaptive Machine Learning; SAP Production Planning; Lean Manufacturing; Real-Time Inventory Optimization; Stochastic Approximation; Production Scheduling; Inventory Control; Non-Convex Optimization; Adaptive Optimization.

INTRODUCTION

1.1 Background

Production planning has progressively shifted from static planning procedures toward data-driven decision environments in which production quantities, inventory levels, replenishment decisions, and scheduling priorities must respond to continuously changing operational information. In an SAP-enabled manufacturing environment, planning decisions can be represented as

interconnected optimization problems involving demand, material availability, production capacity, lead times, inventory positions, and operational priorities. The central challenge is therefore not simply to calculate an optimal production plan, but to repeatedly update that plan as new information becomes available.

Lean production emphasizes the reduction of unnecessary inventory, waiting time, overproduction, and inefficient

resource utilization. However, aggressive inventory reduction can increase the risk of stockouts when demand or supply conditions become uncertain. Consequently, lean production planning requires an adaptive balance between inventory efficiency and operational resilience. Machine learning provides an opportunity to establish such adaptability because model parameters can be updated as new observations become available rather than relying exclusively on fixed planning rules.

The theoretical basis for adaptive learning is strongly connected with stochastic approximation. Bach and Moulines (2011) demonstrate the importance of non-asymptotic analysis in stochastic approximation for machine learning, while their later work examines convergence rates under non-strongly-convex smooth conditions (Bach and Moulines, 2013). These principles are relevant to production planning because operational data are inherently variable and optimization algorithms must learn from incomplete and changing information.

1.2 Problem Statement

Traditional production planning can become inefficient when planning parameters fail to reflect rapidly changing demand, production conditions, or inventory behavior. A fixed safety-stock rule, for example, may be suitable under stable demand but inefficient during abrupt demand changes. Similarly, a production schedule optimized once may become suboptimal after material shortages, machine disruptions, or unexpected orders.

The research problem addressed in this study is therefore the development of a theoretically grounded adaptive machine learning framework capable of continuously updating SAP-oriented production planning and inventory decisions while preserving lean operational objectives. The problem is particularly challenging because the optimization process may be stochastic, non-convex, and subject to noisy gradients. Bassily et al. (2018) highlight convergence behavior in non-convex over-parameterized learning, while Cheridito et al. (2021) demonstrate that stochastic gradient-based learning can also exhibit non-convergence under particular conditions. These findings indicate that adaptivity cannot be treated independently from optimization stability.

1.3 Research Relevance

The relevance of this research derives from the need to connect enterprise production planning with adaptive computational intelligence. Rather than treating SAP as a static planning repository, the proposed approach conceptualizes SAP production and inventory information as a continuously updated decision environment. Machine learning models can use historical and real-time

observations to estimate changing operational relationships and subsequently support production and inventory optimization.

The convergence perspective is particularly important. Absil et al. (2005) establish convergence properties for descent methods involving analytic cost functions, while Attouch and Bolte (2009) examine convergence of proximal algorithms for nonsmooth optimization. Together, these studies support the view that adaptive planning models require explicit consideration of optimization structure rather than simply maximizing predictive accuracy.

1.4 Objectives

The primary objective is to develop an adaptive machine learning framework for lean SAP production planning and real-time inventory optimization. The specific objectives are to formulate production and inventory planning as an adaptive optimization problem, establish a machine learning architecture for continuously updating planning decisions, integrate lean objectives into the optimization function, analyze convergence and stability considerations, and evaluate the expected operational implications of adaptive planning.

1.5 Scope and Significance

The scope encompasses machine learning-assisted production planning, inventory optimization, scheduling adaptation, and optimization stability within an SAP-oriented manufacturing context. The study does not claim implementation in a specific commercial SAP installation; instead, it develops a research framework that can guide such implementation.

The significance lies in integrating lean operational objectives with the mathematical foundations of adaptive machine learning. The framework emphasizes that real-time optimization should not be defined solely by speed. A useful planning system must also maintain stability, avoid excessive parameter oscillation, and provide decisions that remain operationally feasible.

LITERATURE REVIEW

2.1 Optimization and Convergence Foundations

The supplied literature establishes a substantial theoretical foundation for optimization-based machine learning. Absil et al. (2005) investigate convergence of descent-method iterates for analytic cost functions, demonstrating why the mathematical properties of the objective function influence the behavior of iterative optimization. In a production planning context, this principle implies that a cost function combining inventory holding, shortage, production deviation, and scheduling penalties should be designed with optimization behavior in mind.

Bertsekas and Tsitsiklis (2000) examine gradient convergence when optimization contains errors. This is directly relevant to real-time SAP planning because production data can contain measurement errors, delayed updates, forecast inaccuracies, and incomplete information. A practical optimization model must therefore remain useful when gradients or input information are imperfect.

Attouch and Bolte (2009) provide a convergence perspective for proximal algorithms involving nonsmooth functions, while Chill et al. (2009) examine the Łojasiewicz-Simon gradient inequality for gradient-like evolution equations. These contributions are important because manufacturing optimization frequently contains discontinuities or nonsmooth penalties associated with capacity limits, stockout penalties, production thresholds, and discrete planning decisions.

Aujol et al. (2023) further analyze convergence rates of the heavy-ball method under the Łojasiewicz property. Their work provides a theoretical basis for acceleration while simultaneously emphasizing the mathematical conditions required for reliable convergence.

2.2 Stochastic and Adaptive Learning

Bach and Moulines (2011) provide a non-asymptotic analysis of stochastic approximation algorithms, establishing an important foundation for learning under finite-sample conditions. This is especially relevant to production environments because an adaptive planning model cannot assume access to an infinite or stationary data stream.

Bach and Moulines (2013) extend this perspective to non-strongly-convex smooth stochastic approximation and investigate an $O(1/n)$ convergence rate. For inventory optimization, where the objective may not possess strong convexity, this provides useful theoretical motivation for designing learning procedures that remain effective without overly restrictive objective-function assumptions.

Benaïm (1999) examines the dynamics of stochastic approximation algorithms, emphasizing the relationship between stochastic recursive processes and their underlying dynamical systems. Benveniste et al. (1990) similarly establish a comprehensive theoretical foundation for adaptive algorithms and stochastic approximation. Together, these studies support continuous parameter adaptation as a legitimate methodological foundation for dynamic production planning.

2.3 Deep and Non-Convex Learning

Arora et al. (2019) investigate implicit regularization in deep matrix factorization, illustrating that learning dynamics can produce particular solution characteristics

even when explicit regularization does not completely determine the outcome. This insight is relevant to production optimization because a model's training trajectory can influence the operational solutions it generates.

Bassily et al. (2018) analyze exponential convergence of stochastic gradient descent in non-convex over-parameterized learning, whereas Cheridito et al. (2021) identify conditions under which stochastic gradient descent may fail to converge in deep neural network training. The contrast between these studies highlights a central research gap: adaptive production planning requires both learning flexibility and explicit safeguards against unstable optimization.

Chizat et al. (2019) investigate lazy training in differentiable programming, showing that optimization behavior can depend substantially on how model parameters evolve. Chouzenoux et al. (2023) extend convergence analysis to stochastic optimization in non-convex settings through a Kurdyka-Łojasiewicz framework. Collectively, these studies suggest that adaptive SAP optimization should not treat machine learning as an independent prediction component. Learning dynamics and optimization stability must be considered as integral components of the planning architecture.

2.4 Research Gap and Theoretical Positioning

The supplied references predominantly address mathematical foundations of machine learning optimization rather than SAP production planning or lean inventory control. This creates both a limitation and an opportunity. The literature provides strong theoretical tools for constructing adaptive optimization mechanisms, but it does not directly formulate an SAP-centered production and inventory framework.

The proposed research addresses this gap by transferring principles of stochastic approximation and convergence-aware optimization into a manufacturing planning architecture. The framework therefore positions adaptive machine learning as a decision-optimization layer rather than merely a demand-prediction component. Its central theoretical proposition is that real-time planning quality depends jointly on learning adaptability, optimization stability, and operational feasibility.

3. METHODOLOGY

3.1 Research Design

This study adopts a conceptual and analytical research design. The methodology translates the optimization principles established in the supplied literature into an adaptive production-planning architecture. The framework

is organized into five functional layers: data acquisition, state representation, adaptive learning, constrained optimization, and SAP-oriented decision execution.

The design follows a closed-loop principle:

Operational Data → State Estimation → Machine Learning Update → Optimization → Production/Inventory Decision → New Operational Data

This loop allows the model to continuously revise its planning assumptions rather than generating a single static production plan.

3.2 Input and State Representation

The model represents the production environment at time (t) using a state vector:

$$S_t = [D_t, I_t, C_t, L_t, O_t, R_t]$$

where (D_t) represents demand information, (I_t) inventory status, (C_t) production capacity, (L_t) lead-time information, (O_t) open production or purchase requirements, and (R_t) operational constraints.

The state vector can be updated whenever new transactions or planning signals become available. For example, an unexpected customer order increases (D_t), while a material receipt changes (I_t). A machine-capacity reduction modifies (C_t). The adaptive model therefore operates on a changing state rather than a fixed dataset.

3.3 Adaptive Learning Layer

The learning parameters are represented by (θ_t). An adaptive update can be expressed generally as:

$$\theta_{t+1} = \theta_t - \eta_t \nabla F_t(\theta_t)$$

where (η_t) is the learning rate and (F_t) is the time-dependent planning objective.

The use of stochastic updates is supported by the stochastic approximation foundations of Bach and Moulines (2011, 2013), Benaïm (1999), and Benveniste et al. (1990). The adaptive mechanism should permit learning rates and model parameters to change according to observed operational variability.

For example, if demand becomes highly volatile, the model may assign greater importance to recent observations. During stable periods, more conservative parameter

updates can prevent unnecessary changes to established production plans.

3.4 Lean Optimization Objective

The optimization function combines multiple operational objectives:

$$F(\theta) = w_1 C_I + w_2 C_S + w_3 C_P + w_4 C_D + w_5 C_T$$

where (C_I) represents inventory cost, (C_S) shortage or service-risk cost, (C_P) production cost, (C_D) deviation from production requirements, and (C_T) throughput-related cost or penalty.

The weights ($w_1, \dots, w_5$) determine the relative importance of each objective.

The lean principle is represented primarily through inventory and unnecessary production penalties. However, minimizing inventory alone would be inappropriate because extremely low inventory can increase shortages and production instability. The objective therefore treats inventory reduction as one component of a broader operational balance.

3.5 Real-Time Inventory Optimization

Inventory decisions are continuously recalculated using the updated state (S_t). A simplified inventory transition can be represented as:

$$I_{t+1} = I_t + Q_t - R_t$$

where (Q_t) denotes incoming production or replenishment quantity and (R_t) denotes consumption or demand fulfillment.

The adaptive model determines (Q_t) based on predicted requirements, current inventory, production capacity, and risk conditions. A sudden increase in demand, for instance, can cause the model to increase planned production or replenishment before a conventional periodic planning cycle would normally respond.

3.6 Optimization Stability and Convergence

Optimization stability is a central component of the framework. Absil et al. (2005) demonstrate the relevance of convergence properties for descent methods, while Attouch and Bolte (2009) provide a foundation for nonsmooth

optimization through proximal methods. Consequently, the proposed architecture should incorporate convergence monitoring rather than allowing unrestricted parameter updates.

A practical convergence criterion can be defined as:

$$|\theta_{t+1} - \theta_t| < \epsilon$$

for a sufficiently small tolerance (ϵ) over a defined observation interval.

If parameter changes become excessively large, the system can reduce the learning rate or activate a more conservative optimization procedure. Conversely, when the model adapts too slowly to significant demand changes, controlled acceleration mechanisms can be considered. The heavy-ball analysis of Aujol et al. (2023) provides theoretical motivation for examining acceleration while maintaining convergence conditions.

3.7 Handling Non-Convexity and Noise

Production planning is often non-convex because of nonlinear relationships, discrete production decisions, capacity constraints, setup requirements, and conflicting objectives. The proposed methodology therefore does not assume that the objective is globally convex.

The non-convex learning literature provides two important lessons. Bassily et al. (2018) demonstrate that favorable convergence behavior can occur under specific conditions, whereas Cheridito et al. (2021) warn that stochastic gradient descent may fail to converge. Therefore, the framework requires monitoring of objective values, gradient behavior, parameter changes, and decision feasibility.

Chouzenoux et al. (2023) provide an additional theoretical basis for convergence analysis in stochastic non-convex optimization through the Kurdyka-Łojasiewicz perspective. This supports the use of convergence-aware mechanisms rather than assuming that every adaptive learning process will naturally stabilize.

3.8 SAP Decision Integration Concept

The framework treats SAP as the operational execution environment for recommendations generated by the adaptive optimization layer. The machine learning layer receives relevant production and inventory states, computes updated recommendations, and returns decisions such as production quantities, replenishment priorities, scheduling adjustments, and inventory targets.

The integration should remain decision-oriented rather than allowing the learning model to operate without operational constraints. For example, a model might mathematically recommend a large production increase in response to demand, but the SAP planning environment must constrain that recommendation according to available capacity, materials, lead times, and production requirements.

3.9 Hypothetical Operational Example

Consider a manufacturing plant producing three product families. Initially, the adaptive model observes stable demand and maintains moderate inventory buffers. A sudden increase in demand for one product changes the observed demand state. The model increases the predicted requirement and recalculates production quantities while simultaneously evaluating material availability.

If sufficient capacity exists, production is increased. If capacity is constrained, the optimizer prioritizes products according to service risk and economic importance. If inventory for another product is excessive, production can be reduced for that product, thereby supporting the lean objective without compromising overall throughput.

The example demonstrates the principal difference between static and adaptive planning: the decision is generated from the current operational state rather than being based exclusively on historical planning parameters.

RESULTS

The analytical evaluation of the proposed framework produces four principal findings. First, adaptive learning provides a stronger conceptual fit for real-time production planning than a purely static optimization procedure. Because the operational state changes continuously, the decision function must also be capable of updating its parameters. The stochastic approximation literature supports this adaptive perspective by treating learning as a dynamic process rather than a one-time estimation exercise (Benaïm, 1999; Benveniste et al., 1990; Bach and Moulines, 2011).

Second, lean inventory optimization should be formulated as a multi-objective problem rather than as simple inventory minimization. Reducing inventory without accounting for shortages, production capacity, and service requirements can produce undesirable planning outcomes. The proposed objective therefore balances inventory cost with shortage risk, production deviation, and throughput-related considerations. This structure allows the adaptive model to seek efficient inventory levels without encouraging excessive stock reduction.

Third, convergence monitoring emerges as a fundamental requirement. Gradient-based learning can provide efficient updates, but the supplied literature demonstrates that convergence behavior depends on the mathematical and stochastic characteristics of the optimization problem. Descent convergence results from Absil et al. (2005), gradient methods with errors from Bertsekas and Tsitsiklis (2000), and non-convex stochastic optimization findings from Bassily et al. (2018) collectively indicate that uncontrolled updates may be unsuitable for operational planning. The proposed framework therefore incorporates parameter-change monitoring, learning-rate adjustment, and feasibility checks.

Fourth, the framework indicates that adaptability and stability must be treated as complementary objectives. Excessively slow adaptation can leave production plans misaligned with current demand, whereas excessive adaptation can generate unstable production schedules and unnecessary inventory movements. The convergence concerns raised by Cheridito et al. (2021) reinforce this trade-off. A practical system should therefore use controlled adaptation rather than maximizing responsiveness without constraints.

From a planning perspective, the expected operational effect is a more responsive decision cycle. Demand changes can trigger earlier production adjustments, excess inventory can influence future production quantities, and capacity constraints can be incorporated into updated recommendations. The resulting architecture is particularly relevant for environments in which inventory and throughput objectives frequently conflict.

The findings also indicate that the theoretical contribution is stronger than a simple machine learning forecasting model. The proposed framework connects learning dynamics, stochastic approximation, convergence analysis, and enterprise planning decisions. Its central contribution is consequently an adaptive optimization perspective in which machine learning continuously informs planning while mathematical safeguards constrain instability.

However, the findings are conceptual rather than empirical. No real SAP transaction dataset, production database, or controlled industrial experiment was supplied. Therefore, quantitative improvements in inventory turnover, service level, throughput, or planning accuracy cannot be claimed as experimentally demonstrated outcomes. Such metrics must be validated through future implementation and benchmarking.

DISCUSSION

The findings support the proposition that adaptive machine learning can provide a theoretically coherent mechanism for

improving lean production planning when it is integrated with convergence-aware optimization. The main theoretical implication is that production planning should be understood as a dynamic optimization problem rather than a static forecasting problem. Demand, inventory, production capacity, and replenishment conditions evolve continuously; consequently, a fixed model can become progressively less representative of the operational state.

The literature also reveals an important trade-off between learning flexibility and optimization stability. Arora et al. (2019) show that learning dynamics can impose implicit regularization effects, indicating that optimization trajectories influence model behavior beyond the explicit objective function. In a production environment, this suggests that the path through which a model learns may affect the planning policies it ultimately produces. Model training should therefore be evaluated not only according to final prediction error but also according to decision stability.

The role of stochastic approximation is equally important. Bach and Moulines (2011, 2013) establish a foundation for analyzing learning under stochastic conditions, while Benaïm (1999) and Benveniste et al. (1990) provide broader theoretical perspectives on adaptive stochastic systems. These principles support continuous model updating but also imply that parameter adaptation must be carefully controlled. Real-time production data are unlikely to be perfectly stationary, making an adaptive mechanism desirable; however, excessive sensitivity to short-term noise could generate unnecessary production changes.

The convergence literature provides an additional safeguard. Absil et al. (2005), Attouch and Bolte (2009), Chill et al. (2009), and Aujol et al. (2023) collectively indicate that optimization behavior is closely connected to objective-function properties and algorithmic structure. This is particularly significant for SAP planning because operational objectives can contain nonsmooth constraints and competing penalties. A convergence-aware architecture can therefore reduce the risk of producing rapidly changing recommendations that are mathematically driven but operationally impractical.

The contrast between Bassily et al. (2018) and Cheridito et al. (2021) is particularly informative. Favorable convergence results should not be generalized to all non-convex stochastic learning problems. The possibility of non-convergence means that production deployment requires explicit monitoring. A model that fails to stabilize could generate oscillating inventory targets, repeated scheduling changes, or inconsistent production recommendations.

The practical implication is that adaptive machine learning should function as a controlled decision-support mechanism. SAP-oriented constraints should remain

authoritative, while the machine learning layer provides continuously updated estimates and optimization recommendations. This arrangement reduces the risk of allowing a statistically sophisticated but operationally unconstrained model to override manufacturing realities.

Several limitations remain. First, the framework has not been empirically validated using real production data. Second, the supplied literature is primarily mathematical and optimization-oriented rather than SAP-specific, meaning that the enterprise integration component remains conceptual. Third, non-convex optimization may involve local solutions rather than globally optimal decisions. Finally, real-time deployment requires reliable data pipelines, computational resources, and governance mechanisms capable of validating automated recommendations.

Despite these limitations, the framework provides a useful theoretical bridge between adaptive optimization and lean production planning. Its primary contribution is the integration of real-time learning with convergence-aware decision optimization, establishing a basis for future empirical testing.

CONCLUSION

This research proposed an adaptive machine learning approach for lean SAP production planning and real-time inventory optimization. The framework conceptualizes production planning as a continuously evolving stochastic optimization problem in which operational states, model parameters, and planning decisions are repeatedly updated.

The theoretical synthesis demonstrates that stochastic approximation provides a foundation for adaptive learning, while convergence research provides safeguards against unstable optimization. The proposed architecture combines state estimation, adaptive learning, multi-objective lean optimization, real-time inventory adjustment, convergence monitoring, and SAP-oriented decision execution.

The principal contribution is the integration of these components into a unified planning perspective. Rather than using machine learning only to predict demand, the framework positions adaptive learning within the broader production decision cycle. This enables inventory, production, capacity, and throughput considerations to be evaluated jointly.

Future research should validate the framework using real SAP production datasets and compare adaptive learning against conventional planning approaches. Experimental studies should evaluate inventory reduction, service level, throughput, production stability, forecast responsiveness, computational efficiency, and convergence behavior. Further research can also investigate hybrid optimization

algorithms, explainable decision mechanisms, and adaptive learning-rate strategies for large-scale manufacturing environments.

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