# Intelligent Manufacturing Systems: A Review

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***Abstract*—Manufacturing factories, having continuous pursuit of productivity and quality, often meet challenges in coping with high production complexities and uncertainties. These are the areas in which traditional manufacturing paradigms underperform due to the limitation of human operators' ability to cope with these complexities, uncertainties, understanding/memorizing big data, and also their inability to make time demanding decisions. Intelligent manufacturing systems, on the other hand, can yield superior results compared to traditional manufacturing systems as they are capable of analyzing, self-learning, apprehending complexities and are also able to store and analyze large amounts of data to obtain increased quality of the product and lower production cost while shortening the time-to-market. The aim of this paper is to outline the recent accomplishments and developments in intelligent scheduling, process optimization, control, and maintenance. For each aspect, concepts, requirements, application implemented, and methodologies deployed are also presented.**

***Index Terms*—component, Intelligent Manufacturing Systems, Intelligent Scheduling, Intelligent Prediction and Optimization, Intelligent Control, Intelligent Maintenance**

## I. Introduction

Throughout time, industries have evolved to meet the ever growing demands of the customers, handle higher complexities, and accomplish flexible manufacturing. With the development of automated machinery that came with the third industrial revolution, as seen in Figure 1 [1], manufacturing industries saw a large increase in the production efficiency, decrease in labor and production costs, and an increase in the quality of the product. Even though, with each industrial revolution, the bounds of what manufacturing industries can accomplish has increased significantly, with the rapid development of global industry, manufacturing industries are facing many challenges, such as the higher complexity and flexibility of problem, the increasing human labor cost and the urgent requirement of sustainable production. These problems create bottleneck to the traditional manufacturing system due to the operator's limitations on handling uncertainties, complexity and memorizing large amount of data [2].

An example of these limitations at point is the selection of input parameter settings of machineries and equipment. These parameters are decided often offline (before operation starts) either based on the operators' experience or by the use of a trail-and-error based approach. Even with years of experience, machine operators are unable to handle all possible uncertainties, high complexities, enormous amount of data, and are therefore unable to select the optimal combination. These parameters are also only adjusted online (during the operation) in case of unstable machining conditions. Also, it would be relied upon the operator's experience to pick up on queues such as sounds made by the tools, unexpected vibration of the tool/workpiece in order to diagnose unstable machining conditions and make timely decisions regarding the machining parameters. Typically, these input parameters are also very conservative in order to avoid machine failure. Therefore, the capabilities of these machines can be further enhanced by first selecting the optimal input parameters offline and then continuously monitoring and adjusting them online with the aim of increasing the production efficiency, decreasing labor and machining costs and increasing the quality of the machined products. Similarly, the maintenance costs of traditional manufacturing industries can be further reduced by continuously monitoring the conditions of the machine and predicting their remaining useful life.

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The problems and their solutions listed above can be achieved by using intelligent manufacturing systems as they have the ability to learn, understand complexity, engage in various forms of reasoning, and analyze quality and cost. The integration of traditional manufacturing industries with intelligent systems has been made possible due to the development of enabling technologies. Radio Frequency Identification (RFID) technology has enabled automatic identification of hard resources while wireless sensor networks (WSN) provide the ability to perceive, gather, and process valuable, real-time data generated by machines in manufacturing processes. The information gathered using RFID and WSN can be efficiently communicated to different parts of the manufacturing system using wireless communication technology. Embedded systems and computer control systems (CCs) allow for the seamless communication between a hard resource and a computer numerical control (CNC) [3]. What's more, integrating the automated machinery with the rapid-developed intelligent techniques would take the manufacturing industries towards the next industrial revolution i.e. use of cyber-physical systems. This paper presents the research done in the past decade in intelligent scheduling, process parameter optimization, control, and maintenance. In what follows, this paper will present each of these areas as what methodologies and algorithms are used to deal with such challenges. It is also important to highlight the technologies enable intelligent manufacturing that are bedrock of intelligent manufacturing.

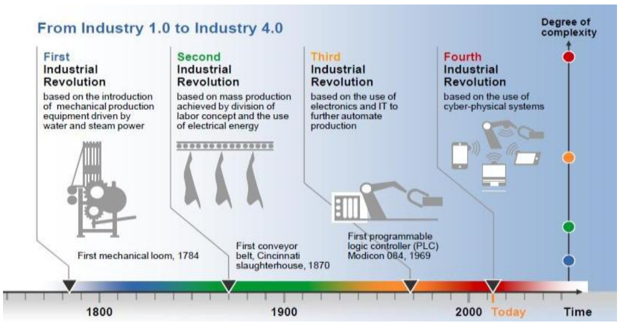


Figure 1. Stages of industrial revolution.

## II. Intelligent Scheduling

Scheduling, defined as the allocation of resources to production tasks with the aim of minimizing key performance indicators (KPIs) such as makespan, tardiness etc. [4], is a complicated yet crucial task in actual industrial production because of the flexible part routing, human and machine interactions etc. [5] Traditional scheduling depends on human operators' ability to make decisions. Traditional scheduling takes significantly longer time on large scale problems and is constrained by the experience of the human operators. Intelligent scheduling systems, on the other hand, are capable of learning from historical production data, understanding the complexity of the scheduling and analyzing the outcome of the schedule. Scheduling problems typically encountered in the manufacturing industries can be split into 3 main categories: 1. Flow shop 2. Job shop and 3. Assembly Job/Flow shop.

In flow shop scheduling problems, there are n jobs with given processing times that are to be processed on m machines in an identical order. Johnson proposed an algorithm in 1954 to find the optimal solution of n-job two machine flow shop scheduling problems. In his algorithm, Johnson proposed that by minimization of the makespan would lead to a minimization of the idle time of the second machine. Tanaka and Yoshida [6] applied Reinforcement Learning (RL) to minimize the maximum completion time, for two and three machines. The authors used inverse of the maximum completion time as the reward function. Their studies showed that an agent could learn and obtain improved schedules even if the formulation is not perfect.

Yagmahan and Yenisey [7] used multi-objective ant colony optimization (ACO) algorithm, a ACO-based optimization algorithm hybrid with local searching technique, to solve flow shop scheduling problems with the aim of obtaining minimized makespan and total flow-time. When tested on a variety of flow shop benchmark problems, their proposed algorithm had superior results in terms of better objective value as well as computational time compared to GA and other algorithms presented in literature. Pan et al. [8] proposed a discrete artificial bee colony algorithm (DABC) to minimize the weight earliness and tardiness penalties in flow shop scheduling problem. In their proposed method, they also used to lot-stream i.e. splitting of jobs into sublots to minimize the objective functions. Their proposed DABC had much better performance in terms of objective value for all the 20 test problems when compared to hybrid GA (HGA) and had significantly better performance in 18 out of the 20 problems when compared to hybrid discrete PSO (HDPSO). Mirsanei et al. [9] proposed a novel simulated annealing (NSA) algorithm with new operators for generating new solutions to minimize the makespan of a hybrid flow shop i.e. flow shop with parallel machines, while considering sequence-dependent setup time. The proposed NSA had better makespan in 93% of the problems when compared to immune algorithm (IA) and a better makespan in 84% of the problem when compared to GA. The proposed NSA also had better computational time in all the test problems compared to IA and GA.

In job shops, unlike flow shops, the n jobs on the shop floor can have completely different processing orders on the m machines available. Job shop scheduling problems (JSSP) have also benefitted from the emergence of intelligent techniques. Banharsakun et al. [10] proposed an improved ABC by biasing its search direction towards the current best solution rather a neighboring solution (that is used in classical ABC) to solve JSSP. The authors used their method on a total of 62 different JSSP benchmark problems and also compared their results with Hybrid Intelligent Algorithm (HIA), Hybrid Evolutionary Algorithm (HEA), HGA, and Improved ABC (IABC). Their algorithm was able to find the best known solution for 51 out of the 62 benchmark problems and also had better performance on 19 problems compared to the other algorithms. Niu et al. [11] proposed an Enhanced Intelligent Water Drops (EIWD) algorithm for minimizing the makespan for JSSP. The authors proposed five new schemes for improving IWD i.e. diverse soil and velocity, bounded local soil, elite global soil update, conditional probability computation, and combined local search. The authors tested their proposed EIWD on 43 benchmark problems and were able to obtain the optimal solution for 37 of them with low computational efficiency. Lin et al. [12] created a robust algorithm to solve JSSP by combining, PSO and SA and also enhancing the features of the algorithms. When tested on 43 benchmark problems, the authors were able to obtain the optimal solutions for 37 problems and in 35 scenarios the solutions found by the proposed algorithm were better than algorithms such as HGA, HEA, and HIA.

Another type of scheduling problem that has received researchers' attention is job/flow shop with assembly. In assembly job/flow shop there is an additional assembly step in which the final product is made by assembling all the jobs. Tian et al. [13] proposed a discrete PSO (DPSO) with redefined particle velocity ad representation to optimize the makespan and mean completion time in two-stage assembly scheduling problem. When compared to techniques such as SA, tabu search (TS), novel PSO (NPOS) their proposed algorithm had better performance as the number of jobs increased i.e. the complexity of the problem increase. Yan et al. [14] used an electromagnetism-like (EM) algorithm for minimizing the weighted sum of makespan, earliness, and lateness of a two-stage assembly flow shop. To have better local search capabilities, the authors used a variable neighborhood search (VSN) in each iteration of EM. When compared to just EM and VSN, the hybrid EM-VSN algorithm had better objective value. Torabzadeh and Zanideh [15] used a cloud based SA (CSA) for minimize the sum of makespan and mean completion time in two-stage assembly flowshop. The proposed CSA showed much better results in terms of objective value and computational efficiency compared to SA when the number of jobs and machines were increased. Wong and Ngan [16] used hybrid Genetic Algorithm (GA) and hybrid particle swarm optimization (PSO) to minimize the makespan for an AJSSP. When applied to a variety of problems, the HGA outperformed the HPSO. Nataranjan et al. [17] proposed and evaluated multiple priority dispatching rules for multi-level AJSSPs. In their study, they changed the weight of the jobs and the utilization percentage of machines to minimize the flowtime and the tardiness. Paul et al. [18] combined dispatching rules such as First Come First Serviced (FCFS), Shortest Processing Time (SPT) etc. and Order Review/Release policies such as Interval Release (IR), Maximum Load (MXL) etc. to optimize three objectives i.e. mean flow time, mean tardiness, and machine utilization for AJSSP. Guo et al. [19] used the combination of mathematical models and GA with a heuristic initialization process, modified crossover and mutation operators, and a new chromosome representation for solving AJSSP. Thaigarajan and Rajendran [20] developed dispatching rules by incorporating the cost of holding and tardiness of jobs to solve dynamic AJSSP.

## III. Intelligent Prediction and Optimization

Though much research has been done to increase the current understanding of the physical principles underlying a process, there are still some processes for which there are no physics-based models available. For these processes, researchers have used intelligent techniques to model the relationship between the input process parameters and their KPIs. Optimization of process parameters, on the other hand, is important tasks as it can help increase the quality, lifespan, and other characteristics of the finished product.

Ozel et al. [21] used NN to model the relationship between the inputs (scan speed, pulse intensity, pulse frequency, and cutting time) and the quality indicators (surface roughness, geometrical and dimensional features, error in volume, and material removal rate) of pulsed laser micromachining. The trained NN was used as a fitness function in multi-objective PSO to minimize the surface roughness and volume error. Mukherjee et al. [22] use PSO for the single and multi-objective optimization of the input process parameters of Nd:YAG laser beam machining (LBM). The authors used equations developed through the use of response surface methodology (RSM), which related the input process parameters (lamp current, pulse frequency, air pressure, pule width and cutting width) to the performance indicators (heat affected zone, taper, upper deviation lower deviation and depth deviation of machined micro-groove) as the fitness function for the PSO. Teixidor et al. [23] used regression analysis to relate the inputs and outputs of pulsed Nd:YAG laser milling. The authors then used the developed equations as the fitness function in PSO with the aim of minimizing the depth error, width error, and the surface roughness. Lin and Chou [24] created an intelligent prediction model for the process of gas tungsten arc (GTA) welding using NNs. In their study, the authors used the electrode angle, welding current, travel speed, and the proportion of mixed flux as the inputs to the NN while the depth and width of the weld bead geometry were used as the quality indicator of the welding operation i.e. outputs of the NN. Once a trained NN was created it was used as a fitness function for GA with the aim of achieving the desired bead width and depth of penetration. Chandrasekhar and Vasudevan [25] used NNs to model the relationship between the inputs (current, voltage, torch speed, and arc gap) and outputs (depth of penetration and weld bead width) of Activated Flux Tungsten Inert Gas Welding (A-TIG). The authors then used GA to find the optimal combination of input parameters that would desired depth of penetration and dead width. Gowtham et al. [26] used adaptive neuro fuzzy inference systems (ANFIS) to map from the input parameters (current, torch speed and voltage) to the performance indicators (bead width, heat affected zone width, and depth of penetration) of A-TIG welding. Next the authors used the trained ANFIS as the fitness function of GA with the aim of achieving the target heat affected zone, depth of penetration, and bead width. Paneerselvam et al. [27] used NNs to map from heating time, heating pressure, upsetting pressure, and upsetting time to the tensile strength and metal loss for the process of friction welding. The authors then utilized PSO, GA, and Simulated Annealing (SA). Tansel et al. [28] used a cluster of NN to represent the friction stir welding operation. In their study, the author used separate NN's to map from the inputs (tool rpm and welding speed) to the outputs (tensile strength, yield strength, elongation, hardness, and heat affected zone). The authors then used GA to search for the optimal combination of tool rpm and welding speed that would either minimize or maximize one of the five outputs while keeping the rest of the outputs within acceptable range. Sedighi and Afshari [29] used mathematical models to map from feed rate, depth of cut, and wheel width to the material removal rate and NN to model from same inputs to the surface roughness of creep feed grinding (CFG). The authors then minimized the surface roughness and maximized the material removal rate for CFG using GA with the mathematical model and NN acting as the fitness function. Lin and Li proposed a new algorithm based on enhanced Pareto PSO and local climbing technique for optimizing the production cost, production rate, and surface roughness in a surface grinding process. Rao and Pawar [30] used ABC, SA, and harmony search algorithms to minimize the production cost, maximize the production rate, and minimize the surface roughness of a grinding process.

## IV. Intelligent Control

As stated earlier, in traditional industrial control systems, manipulated variables are changed manually to adjust the process and minimize the error depending on user's experience. The corresponding problems include time-delay problem, highly dependence on human's decision making and uncertainty of the quality of control schemes. While in the design of intelligent feedback controllers, the requirements include machine learning process based upon the knowledge of human engineers and the ability to identify appropriate controllers and also suggest better alternatives. To achieve these targets, researchers have tried integrating intelligent techniques with traditional controllers and have seen significant improvement in the key performance indicators of different processes such as machining, welding, forging etc.

Kim et al. [31] developed a control algorithm based on fuzzy theory with the aim of maintaining the cutting force constant by adjust the feed rate in an end milling process. The objective of the fuzzy control algorithm was to manipulate the feed rate such that the measured force value was as close as possible to the reference force value. Their experimental results showed that when the feed rate was controlled by the fuzzy logic controller, the resultant force (341.83 N min and 382. 39 N max) varied very little from the reference force value (350 N) while the experiments done without the fuzzy logic controller had a very large deviation (342.33 N min and 412.89 N max) from the reference force value. The fuzzy logic controller (FLC) system showed a 50% improvement in the sampling error over the non-fuzzy logic controller system. Liu and Wang [32] developed a neural network based adaptive controller for the optimization of a milling process to increase robustness and stability. Their objective was to perform an online optimization of the milling speed by utilizing Augmented Lagrange Multipliers (ALM) while keeping the force below a maximum threshold value to increase the milling efficiency, measured by the rate of metal cutting. The milling process was modeled using back propagation neural network (BP NN) and during the milling process. When compared to traditional milling the adaptive milling system improved the milling efficiency by 15%. Zuperl et al. [33] developed a fuzzy adaptive control strategy for high speed end-milling operation. In their proposed strategy, a fuzzy controller was integrated with a CNC machine for optimizing the metal cutting process by maximizing the feed-rate while subjected to constraints of allowable cutting forces on the tool. When comparing the adaptive control strategy to a conventional milling strategy, they saw that in conventional milling, the optimal MRR was only reached during the last step; however, for the adaptive control strategy the average MRR was much closer to the optimal MRR and was improved by 27% compared to the conventional milling strategy. The adaptive controller also had a much higher average feed and the cutting force was also constant at around. Zurpel et al. [34] combined NN, fuzzy logic, and particle swarm optimization (PSO) algorithms for modeling and adaptively controlling the process of ball-end milling. In their proposed approach, adaptive neuro-fuzzy inference system (ANFIS) was used to model the milling process and PSO was used to optimize the feed-rate offline. The objective of PSO was to maximize MRR while keeping the cutting force as close to the reference value as possible. During the end milling process, the feed-rate was controlled online using a NN controller whose objective was to keep the cutting forces as close to the reference value. When compared to traditional milling, the adaptive controller had a 27% higher MRR.

Zhang et al. [35] proposed a NN based adaptive controller for online prediction and control of the surface roughness in a milling process. Their prosed supervisory system consisted of two NN subsystems: a neural network based, in process surface roughness prediction (INNS-RP) subsystem and a neural network based, in process adaptive parameter control (INNAPC) subsystem. The INNS-RP was able to predict the surface roughness using feed, speed, depth of cut, and vibration as inputs. The INNAPC, on the other hand, was given the predicted surface roughness as input and it would change the feed rate of the CNC depending on the difference between the predicted and desired surface roughness. When their proposed supervisory system was tested online, they found that the INNS-RP had a 92.42% prediction accuracy and in 100% of the tested cases they were able to achieve a surface roughness value lower than the desired surface roughness. Wang and Sheng [36] developed an online monitoring system to control the surface roughness in the grinding of a ceramic. In their online monitoring system, two sets of NNs were used, ANN1 would take an AE signal as and input along with the cutting depth, wheel speed, and workpiece speed and give an output of the wheel sharpness. The wheel sharpness along with process parameters such as roughness target, cutting depth, and crossfeed were given as input to ANN2 which would predict the optimized workpiece and wheel speed. The surface roughness obtained using the online monitoring system were much closer to the desired surface roughness when compared to the surface roughness obtained without using a monitoring system.

Messler et al. [37] developed used FL to develop an intelligent control system for automatic resistance spot welding (RSW) with the aim of compensating for errors and variations encountered during the process. In their intelligent system, a FLC was used to adjust the power delivered into the weld depending on the deviation of electrode displacement and electrode velocity compared to the desired values. They tested their proposed system under five different experimental conditions and in all 5 of the conditions, their proposed system was able to maintain the power input such that the actual outputs were very close to the desired outputs thereby increasing the quality of the part compared to a system where the FLC was not used. Ding et al. [38] proposed a system based on fuzzy reasoning to address the issue of wire extension stability in MIG welding process. The fuzzy PID controller system would automatically change the wire feed speed in real-time thereby stabilizing the welding process. Di et al. [39] +created a fuzzy logic based system to control the gas tungsten arc welding (GTAW) process. In their system, a FLC was trained using a NN to fine-tune the membership functions of the FLC and automate the fuzzy logic rule generation process. The FLC system was used to control the welding current based on the deviation of the welding pool width from the reference value. The FLC system developed by them was superior to other approaches such PI control, FLC without on-line tuning etc. Yan and Wun [40] established a sensing and control system for pulsed gas metal arc welding (P-GMAW). In their system, they used a Current Inspiriting Backside Width Neural Network model (CIBWNNM) based model to predict the weld pool width on the backside of the workpiece (Wb) with the input parameters being the current, the topside weld pool width, and the topside weld bead mean height. The predicted Wb was measured against a reference back side weld pool width and the error in the value along with the change in error was used to adjust the welding current. Online testing of their system showed that the proposed sensing and controlling system was able to control the welding current such that Wb was extremely close to the reference value of 5 mm. In their experiments, Wb had a mean error of 0.25 mm, and a maximum error of 0.47 mm. Zheng et al. [41] applied a self-tuning fuzzy PID controller to tune the input parameters of a Switched Reluctance Motor (SRM) direct drive volume control hydraulic press. Depending on the value of error and change in error the values of the proportional, integral, and the derivative gains would be adjusted to improve various aspects for the volume control electro-hydraulic servo system driven by the SRM directly. When compared to a traditional PID system, their fuzzy PID system had much lower error amplitude, lower steady-state displacement error, and has superior response speed as well as anti-disturbance ability. Garcia designed a system based on artificial intelligence to automate supervision diagnosis and control in sheet metal stamping process. Hau and Choi [42] used a fuzzy logic-based controller system for adaptive deposition during a direct metal/material deposition (DMD) process. The FLC would change the laser power to maintain the deposition height close to the reference value. When their system was tested online, the average height error of the FLC was within 0.050 mm showing that the proposed system is capable of building 3D parts with nonlinear geometry with high accuracy. Perez and Cana [43] created a control system that would minimize some of the limitations of laser surface heat treatment such as lack of uniformity in treatment due to external disturbances, imperfections in treated element etc. They used a fuzzy logic controller to adjust power supplied to the laser depending on the difference between the actual temperature and the reference temperature. Their results showed that the system temperature when controlled by fuzzy logic deviated very little from the reference temperature under stable experimental and actual conditions.

## V. Intelligent Maintenance

In manufacturing, machines suffer increasing wear with usage and age, which leads to low reliability and high operational cost [44]. A failure in these machines lead to a decrease in productivity, increase in production cost as well as timely services to customers [45]. These failures can also cause catastrophic damage, personal and environmental if they remained unchecked for an extended period of time. Maintenance strategies can be classified into two categories, corrective maintenance (CM) and preventive maintenance (PM). In CM, the maintenance is performed after the breakdown of equipment. PM can further be classified into scheduled maintenance and condition-based maintenance (CBM). In scheduled maintenance, maintenance is carried out at certain times where parts are lubricated, calibrated, and replaced. In CBM, the machines are continuously monitored in real time in order to detect faults. Before appropriate steps can be taken for maintenance, a correct diagnostic of the machinery is essential as unnecessary maintenance can decrease productivity and increase operational costs. Therefore, researchers have also focused on creating accurate models for machine diagnostics and prognostics.

Sun et al. [46] Tran and Yan [47] used a combination of wavelet transform and SVM (WSVM) for diagnostic and prognostic of rotating machinery. For fault diagnostics, the authors performed component analysis on the vibration data using six accelerometers and used the results as inputs for the WSVM classifier. For the prognostics, the authors also used the vibration signals for the remaining life estimation using SVM model in which Gaussian kernel was employed. The developed prognostic model was able to forecast the survival probability of the machine with respect to time. Saravanan et al. [48] compared the prediction capabilities of ANNs and proximal SVM (PSVM) for fault diagnosis of spur bevel gear box. In their studies, the authors first used a decision tree to select the most important features from vibration signal that would be used as inputs to the ANN and PSVM. The results of their case studies showed that the ANN had a 97.5% prediction accuracy while the PSVM had a 97% accuracy, however, the training time required for the ANN was larger than the training time required for the PSVM.

Modeling of maintenance operations has aroused interest from researchers since 1960's to cut down expenses related to maintenance. Yuniarto and Labib [49] proposed a method for PM that utilized fuzzy logic rule-based controller. Their work was based on controlling a failure-prone manufacturing system while proposing which PM method was applicable to a specific failure-prone manufacturing system. They utilized mean time to repair and mean time between failures of the system as the integrating agents. Fouad et al [50] also utilized a FL based system which consists of 44 rules and five inputs for PM in an enterprise resource planning system.

## VI. Conclusion and Future Aspepcts

The case studies presented in this paper show that the integration of traditional manufacturing systems with intelligent techniques, in the expansion of machine learning, prediction and optimization capabilities, have enhance performance levels as compared to just traditional systems and their integration that will enable manufacturing industries to further increase their productivity, increase quality of product, and also meet the rising demand of the consumers. Clearly the intelligent machines and equipment is an indispensable backbone for Industry 4.0 and beyond.

Though these results are very promising, in some of the systems, such as scheduling, the performance of intelligent systems is only tested on benchmark problems. Though benchmark testing is a good start but there is still exists a big gap between benchmark problems and actual production application in terms of uncertainties and complexities. Further, the case studies only demonstrate the integration of intelligent techniques with a single manufacturing system i.e. scheduling, control, maintenance etc. Most manufacturing industries are integrated systems; therefore, these systems will have to communicate with each other in a seamless fashion to reach their fullest potential. This kind of integration will require collaboration of researchers from different areas such manufacturing, information technology (IT), electronics, digital threads, etc. With these collaborations, new challenges will arise such as management related costs, maintenance required with different parts of this newly integrated industry, robust online analysis of big data from actual production.

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