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Research on Process Decision-Making Behavior under Incomplete Information Conditions in Automobile Manufacturing Systems

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Abstract: Facing the multi-stage assembly and inspection problems in automobile production, the actual production and management process often involves multiple factors such as unavailable quality information, machine measurement errors, cycle time correlation between stations, and limited rework capabilities. This leads to typical decision-making characteristics at the workshop level: "experience-triggered thresholds, overly cautious repetitive inspections, and a bias towards short-term output." This paper uses incomplete information as the main constraint and defines a partially observable process decision-making Markov process (POMDP) model, integrating latent quality variables, observed signals, and executed operations within the same model. Furthermore, risk quantification and robustness constraints considering rework and pass/fail indicators are introduced to construct an achievable and executable "confidence state-plan-feedback" loop system. The paper also presents a hybrid computational method of "offline approximation iteration and online rolling optimization" to address the combinatorial explosion of state space and the requirements of real-time computation, and proposes an analytically sound threshold decision extraction scheme. In simulation experiments of typical automotive body component welding operation chains, compared to responsive processing methods and fixed periodic inspection methods, the proposed method demonstrates lower expected cumulative costs and more reliable quality risk control at different detection error levels. The results can be used to guide automotive production lines in understanding and supporting autonomous process decisions under incomplete information during their transformation and upgrading towards digital and intelligent factories.

1. Introduction

Automobile production lines typically consist of multiple steps, including stamping, welding, painting, and final assembly. Typical production lines are characterized by complex processes, tight cycle times, and long quality responsibility chains. For key steps such as welding and final assembly, quality characteristics such as assembly gaps, spot weld strength, torque/angle during tightening, and paint width cannot be measured online in a single, non-destructive manner. Furthermore, even with the aid of online sensors and machine vision, factors such as workpiece reflection, mutual occlusion, temperature drift, and calibration drift can cause significant noise and frame drops in the observed signals. Faced with this situation, the workshop is forced to choose between maintaining production cycle time or halting the line/rework to reduce quality risks. Since the true quality condition is invisible, choices can only be made based on incomplete information, leading to a series of problems such as strategy oscillation, over-inspection, under-inspection, and rework congestion. Therefore, it is necessary to construct a process-level decision-making behavior model for incomplete information and obtain a calculable, explainable, and implementable optimal strategy as a breakthrough to improve the resilience and overall efficiency of the automobile production line system.

Through observation of the manufacturing site and engineering practice, it is understood that process decision-making under incomplete information conditions often exhibits three types of behavior: (1) Threshold triggering: If some observable variables (such as the peak value of the tightening curve, image scoring, fixture offset) reach the empirical threshold, rework or additional inspection is initiated; its characteristics are easy to implement but low noise tolerance and easy to false alarms. (2) Conservative additional inspection: Under the pressure of quality responsibility and accountability costs, managers tend to increase the sampling rate or extend the time to "reduce uncertainty"; this practice will cause serious occupation of cycle time and inspection resources, resulting in hidden losses. (3) Short-term output preference: When the pressure of production capacity increases or when shift changes, material shortages, etc. occur, there is a tendency to release to ensure the flow of WIP; doing so will cause defects to be passed on and accumulate downstream, leading to a rework flood. These choices are essentially proxy responses to "invisible quality status", reflecting the product of the combination of rationality and irrationality under the combined effect of information framework, reward and punishment system and resource constraints. We generalize the behaviors listed above into a partially observable decision problem and hope to intuitively represent their causes in the model.

2 System Description and Information Structure Modeling

2.1 Automobile Manufacturing Process Chain and Quality Transfer Mechanism

Imagine a production line unit consisting of N serially connected systems (e.g., several body assembly stations + final assembly tightening station + online measurement station). Each node exhibits a "generation-amplification-masking" transmission pattern in relation to the overall vehicle quality: small upstream errors may be amplified by downstream assembly interference, or they may be corrected by subsequent tooling and masked in the short term. To describe this process, this paper denotes the actual quality status of the product at process t as x_t, which can be a discrete level (qualified, repairable, scrapped) or a continuous defect measurement. Process behaviors a_t (e.g., release, repair, additional testing, adjustment) affect the state transition probability $P(x_{t+1} | x_t, a_t)$, cycle time, and resource costs. In particular, when we choose to perform a rework operation, the condition improves but occupies the rework station's capacity and introduces uncertainty in reprocessing; when we choose to pass, we can maintain output but leave hidden defects to downstream processes, leading to higher rework costs later.

2.2 Observation Model and Sources of Information Incompleteness

In some observable environments, decision-makers cannot directly observe x_t but can only receive observation signals o_t, such as torque curve characteristics, visual defect scores, welding current/voltage, sound signals, and sampling results. Observations often exhibit three main types of imperfections: first, noise, meaning the probability distribution of observations under the same real-world conditions has a large variance; second, data loss, including sensor disconnections, camera obstructions, or data asynchrony; and third, lag, meaning quality problems often only become apparent after several steps through final or driving tests. This paper uses conditional probability $P(o_t \mid x_t, a_{t-1})$ to characterize the observation process, allowing for behavioral intervention in the observation effect; for example, additional checks can improve the signal-to-noise ratio at the cost of time. For ease of engineering implementation, o_t quantization can be divided into several alarm levels, or continuous signals can be converted into confidence scores in some way.

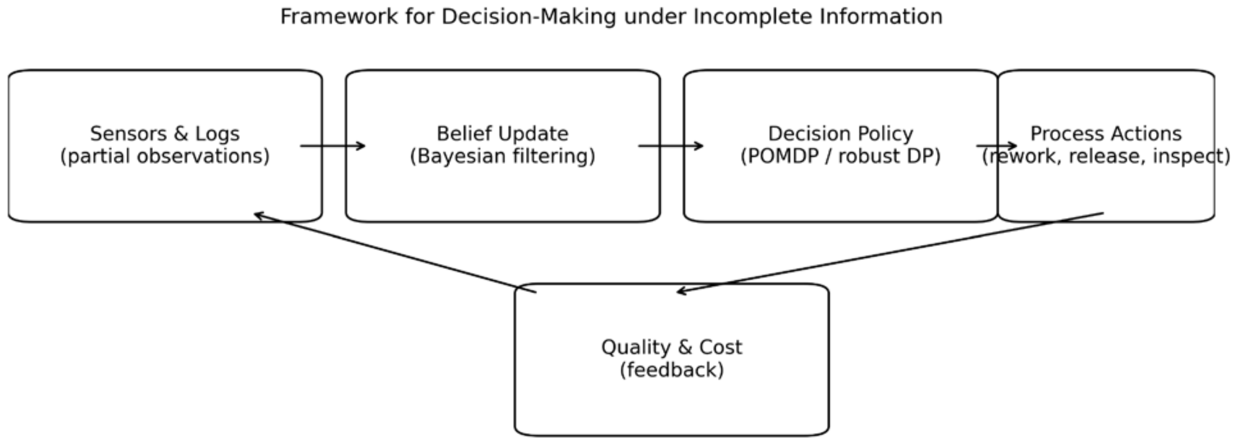

Figure 1. Closed-loop framework for process decision-making under incomplete information conditions.

2.3 Decision-making entities and behavioral assumptions

To focus on process-level decision-making activities, we abstract the decision-making body into a section manager or an intelligent scheduling program. Their goal is to minimize the expected cost throughout the process under specified capacity and quality conditions. The total cost comprises four factors: 1) the cost of cycle time deviation (idle time, deceleration, overtime); 2) the cost of inspection and rework (labor time, materials, energy consumption); 3) the cost of defect leakage (downstream rework amplification losses, scrap); and 4) the risk cost of quality incidents (a proxy indicator for batch rework and recall risks). We also introduce the following behavioral setting: when making decisions, the decision-maker uses a "confidence state" of an invisible state to describe the unknown, and based on this, takes a suboptimal or risk-avoiding choice. This setting is applicable to both the subjective probability assessment of uncertainty by humans during decision-making and the state estimation in intelligent algorithms.

3. Incomplete Information Process Decision Model

3.1 State-Action-Observation POMDP Representation

The process decision is represented as a 7-tuple M = (X, A, O, P, Z, C, γ). Here: X X is the set of latent quality states; A is a set of actions, typically a ∈ { Releas

the observation set; P is the state transition kernel $P\left(x' \mid x, a\right)$, giving the probability distribution of moving from state x to the next state x' when action a is performed; Z is the observation kernel

Z(o|x, a), providing the probability of observing o after performing an action in state x; C is the immediate cost function; and $\gamma \in (0, 1]$ represents the discount At each process, given the current confidence state b_t, the decision-maker chooses an action a_t, the system transitions to x_{t+1}, and an observation is generated o_{t+1}. Because directly X solving this is usually impossible, the core of POMDP is an equivalent MDP with respect to the confidence space B: the confidence b_t is deterministically updated given, allowing dynamic programming (a_t,o_{t+1})on B. This formulation can simultaneously model the manufacturing environment of "incomplete information + actions affecting the quality of information".

Table 1. Definitions of Main Symbols and Variables

Symbol	Meaning	Unit/Type
x_t	True quality state at stage t	Discrete/Continuous
o_t	Observation (sensor score, test result)	Vector
a_t	Action (release/rework/inspect/adjust)	Categorical
$b_t(x)$	Belief over hidden state	Probability
$P(x'\|x,a)$	State transition kernel	Matrix
$Z(o\|x,a)$	Observation likelihood	Distribution
C_t	Immediate cost	Currency/Time
$CVaR_\alpha$	Tail risk measure at level α	Scalar

3.2 Cost Function and Constraints (Quality, Cycle Time, Inventory)

Real-time costs C(xt,at) are used to integrate production metrics. We used the following decomposable structure: $C=c_prod(at)+c_ins(at)+c_rew(xt,at)+c_spill(xt,at)$, where $c_p$rodrepresents cycle time loss (e.g., extra time caused by inspection); $c_i$nsrepresents inspection consumables and man-machine time; $c_r$ew represents the difference in impact of rework operations under various conditions; $c_s$pillrepresents the risk of amplification and scrapping caused by missing defective products. To characterize production line constraints, two types of hard/flexible constraints are considered: (1) Cycle time constraint: the single-station operation time τ (at) is not allowed to exceed the upper bound $T_c$ycle, and the timeout is added to the cost in the form of a penalty function; (2) Resource constraint: the rework station has a capacity limit R. When the number of rework queues qtexceeds the limit, the rework cost increases and may cause priority to rise or fall. In addition, the quality KPI (e.g., the final inspection defect rate is less than or equal to ε) can be converted into an opportunity constraint P (defect at end) <= ε or a tail risk indicator can be used instead.

3.3 Belief State Update and Risk Measurement

Belief update is the bridge between perception and action. Given prior belief b t and action a t, posterior belief updates according to Bayes' rule upon observing o_{t+1}:$b_{t+1}(x')=\eta\cdot Z(o_{t+1}|x',a_t)\cdot\Sigma_x P(x'|x,a_t)\cdot b_t(x)$, where η is a normalizer. In case of missing observations, we rely on the predictive distribution: $b_{t+1}(x')=\Sigma xP(x'|x,a_t)b_t(x)$. To account for occasional low-quality events, we adopt the $CVaR_\alpha$ risk metric: $CVaR_\alpha(L)=\min_\zeta \zeta+(1/(1-\alpha))\cdot E[(L-\zeta)_+]$, where L is the cumulative loss. In manufacturing, L may represent repair cost of defective batches or a proxy of potential recall loss. Incorporating the CVaR into objective can make the policy more conservative as uncertainty increases, which however, should be tuned via α and λ to prevent excessive overinspection.

4 Solution Algorithms and Implementation

4.1 Offline Strategies: Value Iteration/Policy Iteration and Dimensionality Reduction

In the offline process, P and Z are inferred based on historical data and expert experience, and the optimal value function V(b) is solved approximately on the belief space. Since the belief space is a continuous high-dimensional variable, this paper adopts a method based on discrete points to generate a set of typical belief sample points {bi} under representative operating conditions, and then implements value iteration or policy iteration on these typical belief sample points. For the discrete state case, V(b) has a piecewise linear convex structure, which can be expressed as the upper envelope on the α vector, but the number of α vectors will grow explosively under large-scale process networks. Therefore, two compression methods are introduced: (1) State clustering: aggregate states with similar defect levels and unified repair routes. (2) Factor decomposition: decompose the hidden state of product quality into local product defect factors and overall assembly factors and solve them separately under the premise of approximate independence. The offline output includes: approximate value function, policy lookup table and heuristic boundary for online rolling optimization.

4.2 Online Strategy: Rolling Time Domain + Approximate Dynamic Programming

The workshop environment is highly time-sensitive, and solving a complete POMDP often cannot meet the requirements of millisecond to second-level decision-making time windows. This paper utilizes the concept of online rolling time domain: whenever a process arrives, planning is only performed for a limited timeframe of H steps in the future, while using an offline value function approximation $\hat{V}$ as the termination cost. The problem to be solved online is described as follows: $\min_{a_t,\ldots,a_{t+H-1}} E[\Sigma_{k=0}^{H-1}\gamma^k C(b_{t+k},a_{t+k})+\gamma^H \hat{V}(b_{t+H})]$ To further reduce computational load, sampling can be performed on the observed branches (Monte Carlo tree method) or deterministic equivalence can be adopted (using the observation mean instead). In engineering, action suggestions are obtained and updated $b_t$from the MES/PLC/vision end o_t, and then output; if the suggestions violate on-site rules, a strategy of "hard rules first, soft targets adjusted" is adopted to ensure safety and compliance.

4.3 Behavioral Interpretation: Threshold Strategy and Interpretable Rule Extraction

To ensure that the improved solution is understandable and implementable by engineers, this paper extracts interpretability rules from the calculated strategy π(b). Experience shows that the optimal strategy under unit defect factor and single resource constraints typically has a threshold form, meaning that rework or additional detection is only performed when the defect belief b(defect) > threshold θ. Furthermore, this threshold varies with external factors such as the rework queue length q and cycle pressure s. We fit θ = θ0 + θ1·q + θ2·s on {b^i} using action switching boundary counts and output it as a rule table to complete the "model-driven - rule implementation" transformation. Contribution analysis can also be provided: comparing the Q(b,a) differences between different actions indicates whether the factors prompting rework are mainly caused by increased tail risk or by downstream amplification losses from direct passage.

5. Case Studies and Simulation Verification

5.1 Experimental Scenario and Parameter Settings

A standard assembly chain simulation with 10 nodes is established, with the first six nodes being welding/assembly stations and the last four being inspection and preparation stations. The implicit quality state is set to three levels: G (Good), M (Reworkable), and B (Critical Defect); the action space is: Release, Inspect, and Rework. The observation signal is a product quality score between 0 and 1; the score noise distribution is characterized by different means and variances; rework capability is described by a queue on a single server, with its service time following a log-normal distribution. The baseline strategies are: Reactive (rework only when the score is below a set threshold), Periodic Inspection (periodic manual sampling), and Belief-aware (our method).

Table 2 Summary of Simulation Parameters and Main Results

Item	Value	Reactive	Periodic	Belief-aware
Number of stages N	10	10	10	10
CycletimelimitT_cycle	60s	60s	60s	60s
ReworkcapacityR	1station	1station	1station	1station
Observationnoise(std)	0.12	0.12	0.12	0.12
Expectedtotalcost	131.4	131.4	129	109.5
Finaldefectrate	2.90%	2.90%	2.10%	1.60%
AverageWIPdelay	8.4min	8.4min	10.2min	8.9min

5.2 Results Comparison and Sensitivity Analysis

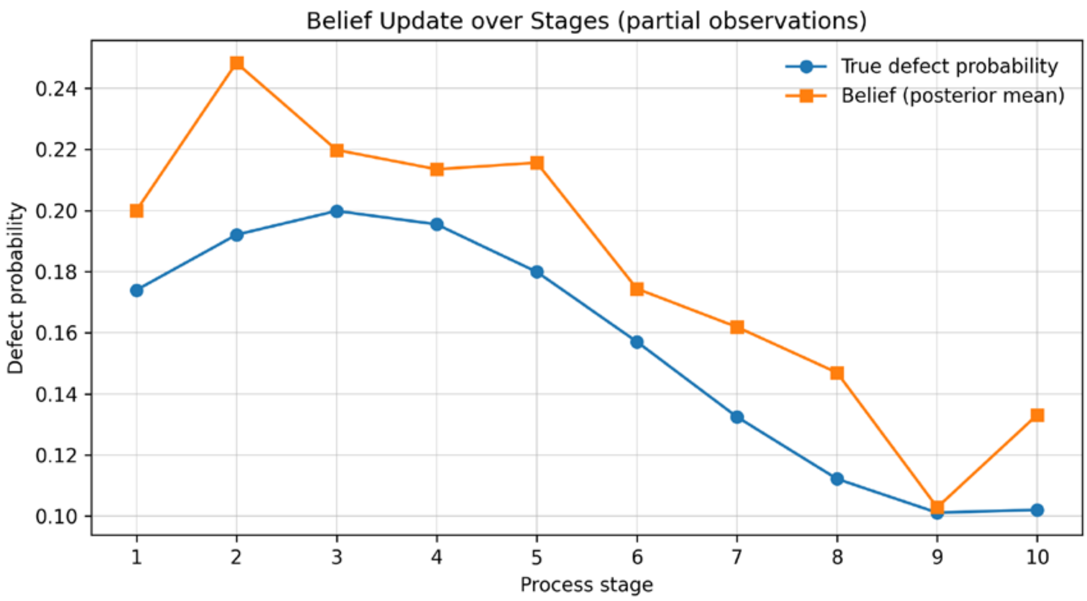

Figure 2. The updating effect of belief state as the process evolves

First, we analyzed the impact of the belief update process on defect rate prediction. Figure 2 shows a comparison of the actual defect rate and the change in posterior belief under partially observable conditions. The figure shows that in the presence of noise, the belief curve has a certain lag effect relative to the true curve, but the general trend is similar; however, when subsequent process observations are more certain, it gradually approaches and converges to the true value to guide subsequent actions. Next, we compared the performance of various methods in terms of average total loss under fluctuating observation noise. As shown in Figure 3, the reactive strategy experiences the fastest loss growth with increasing noise, because it suffers from both false alarms/rework and oversights; the periodic inspection method is more robust, but incurs redundant detection costs under low noise conditions. Our algorithm can dynamically adjust the detection and rework intensity based on the current belief level and risk level, thus achieving minimum loss at various noise levels and a flatter, more stable curve.

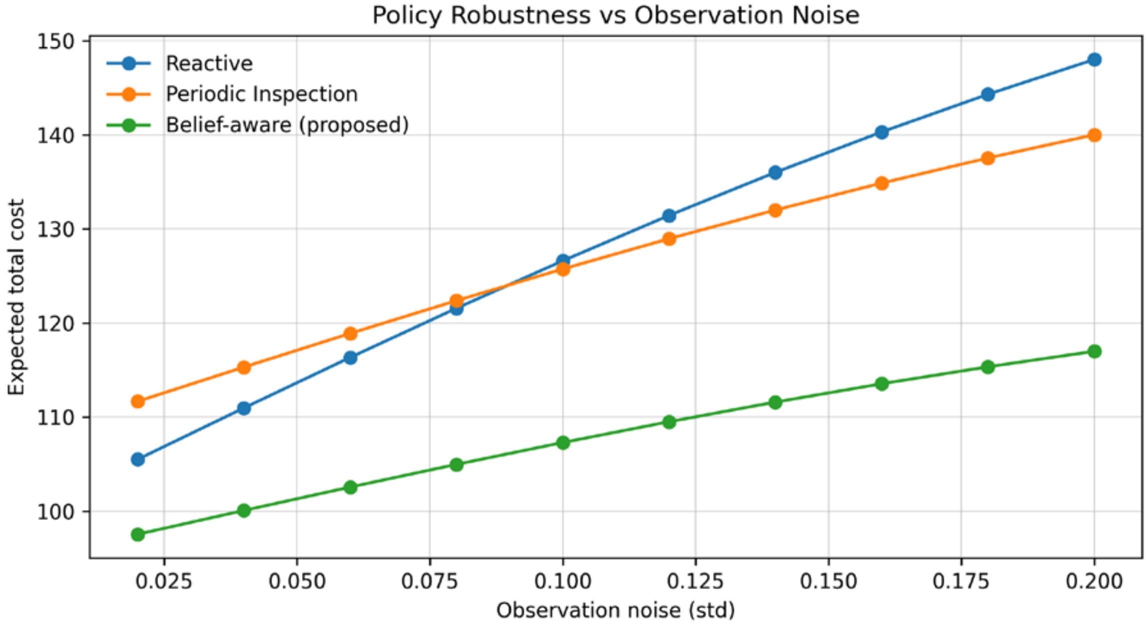

Figure 3. Comparison of robustness of different strategies under observation noise

5.3 Management Implications and Implementation Pathways

From a manager's perspective, this paper offers three feasible insights. First, quality management should not rely solely on "post-event discovery and rework," but should integrate fragmented process information into risk assessment indicators through belief updates, thereby enabling feedforward control of latent defects. Second, inspection plans need to be linked to production line load: fewer inspections can be added when cycle time is tight and confidence levels are low, while intervention should be initiated as early as possible to mitigate concentrated outbreaks when confidence levels improve or the rework queue approaches congestion. Third, a "gradual" approach should be adopted in deployment: initially, offline analysis should be used to provide threshold rules and suggested dashboards, then gradually introducing rolling optimization modules and ultimately connecting to a closed loop MES/APS/quality traceability system. At the data level, it is recommended to construct a minimal necessary dataset (core workstation sensors, sampling results, rework records, cycle time/work-in-process) supplemented by routine calibration and gap filling measures to improve observation.

6. Conclusions and Outlook

This paper addresses the decision-making problem under incomplete information conditions in the automotive production process chain. It proposes a unified modeling framework based on POMDP, jointly modeling the quality Markov hidden state, observation noise, and process operations, and forming a closed loop of "data-cognition-decision" based on belief updates. The objective function simultaneously considers tail risk measures and resource/cycle time constraints. This allows the solved strategy to automatically adjust to balance average loss and extreme quality events. Simulation examples show that, compared to responsive and periodic solutions, the proposed method achieves lower expected total cost and more robust quality control under different levels of observation noise.

The next step can be carried out in three aspects: (1) Multimodal heterogeneous data-driven: increase the observation variables such as vision, force/sound signals, process indicators and manual inspection text, and on this basis, carry out refined state estimation and detect and perceive faults based on uncertainty; (2) Group decision-making process modeling: establish corresponding hierarchical partially observable Markov decision-making processes or multi-player game models for process level, section level and supply chain level to characterize the reward function and information transmission mode between subjects; (3) Physical simulation and online A/B testing: deploy the proposed strategy on the digital twin production line, implement online learning and control experiments with safety restrictions to test the benefits, and complete the iterative cycle of "model-strategy-test".

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