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HIERARCHICAL PARETO OPTIMALITY APPROACH FOR INTELLIGENT CONTROL SYSTEM IN OIL MANUFACTURING

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Abstract. In this paper, we present a hierarchical Pareto optimization approach for an optimal control system of a complex dynamic hierarchical oil refinery system. Due to the hierarchical structure of the oil refinery, the standard Pareto principle can solve the multi-objective optimization problem of one process without considering the impact of the results on the other processes, since our goal is to achieve the optimal control for the whole system. Each subsystem contains a process, which is considered as a sequence of processes leading to production based on the previous process. The hierarchy Pareto principle is used to select the optimal control variables in the control system. The application of the hierarchical Pareto principle to the process of oil refining is more significant in the selection of control variables used in the system. The results of the system are presented in the form of a set of configurations described as the Pareto front of a system with hierarchical structure. The Pareto principle in this work can be used as a tool for control systems in complex and dynamic systems. The proposed approach is part of a larger project using a multi-agent system based on Deep Reinforcement Learning that allows each agent to adapt to the process.

Keywords: Pareto front, multi-objective optimization, neural network, machine learning, oil refinement

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ИЕРАРХИЧЕСКИЙ ПАРЕТО-ОПТИМАЛЬНЫЙ ПОДХОД ДЛЯ ИНТЕЛЛЕКТУАЛЬНОЙ СИСТЕМЫ УПРАВЛЕНИЯ В НЕФТЕПЕРЕРАБОТКЕ

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Аннотация. Представлен подход иерархической Парето-оптимизации для оптимальной системы управления сложной динамической иерархической системой нефтепереработки. Из-за иерархической структуры нефтепереработки стандартный принцип Парето может решить многоцелевую задачу оптимизации одного процесса без учета влияния результатов на другие процессы, поскольку нашей целью является достижение оптимального управления для всей системы. Каждая подсистема содержит процесс, который рассматривается как последовательность процессов, ведущих к производству на основе предыдущего процесса. Принцип иерархии Парето используется для выбора оптимальных управляющих переменных в системе управления. Применение принципа иерархии Парето к процессу нефтепереработки важно при выборе управляющих переменных, используемых в системе. Результаты работы системы представлены в виде набора конфигураций, описанных как фронт Парето системы с иерархической структурой. Принцип Парето может применяться в качестве инструмента для систем управления в сложных и динамических системах. Предложенный подход является частью более крупного проекта, использующего многоагентную систему, основанную на глубоком обучении с подкреплением (Deep Reinforcement Learning), позволяющую каждому агенту адаптироваться к процессу.

Ключевые слова: Парето-фронт, многоцелевая оптимизация, нейронная сеть, машинное обучение, нефтепереработка

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Introduction

In most practical optimization problems, several criteria must be considered to obtain a satisfactory solution [1–5]. As the name suggests, multi-objective optimization aims to optimize multiple objectives simultaneously. These objectives are usually in conflict with each other: the improvement of one objective leads to the deterioration of another objective. Consequently, the final result of the optimization is no longer given by a single solution, but by a set of solutions, each representing a trade-off between the different objectives to be optimized. Given a finite set of solutions, all solutions can be compared pairwise according to the dominance principle, and we can deduce which solution dominates the other [6–9]. In the end, we obtain a set in which none of the solutions dominates the other. This set is called the set of non-dominated solutions [4, 10–12].

Oil production is a complex, hierarchical, dynamic system that begins with crude oil, which is divided into products through a complex process. The main objective of oil production is to produce high quality oil and maximize productivity to achieve high profit. Since an increase in productivity eventually leads to a decrease in quality, Pareto optimality is used to obtain the optimal configuration for each process to maximize profit. Since each process has a subprocess, the optimality of each subprocess alone does not lead to the optimal process [13–15]. To further illustrate this, suppose that each sub-process is a player in a team game, namely oil production. The individual player is at a high level, but the teamwork is not optimal, that is, in order to synchronize the whole team perfectly, each player should cooperate with the rest of the team.

Problem statement

The hierarchy structure of a system consists of levels called subsystems. Each subsystem has its characteristics (process) and its control factors. The goal of each subsystem is to achieve its objectives. We consider our system optimal when all its subsystems are optimal considering the higher-level system.

Let S be our system $S \equiv \langle S_1, S_2, \ldots, S_n \rangle$, where n is the number of sub-systems, then:

$$S_i \Leftrightarrow G_i(u_i) = \left[g_{i1}(u_i), g_{i2}(u_i), \ldots, g_{im}(u_i) \right].$$

Each sub-system S_i has its objectives $G_i(u)$ (where m is the number of objectives) and control factor vector u_i:

$$u_i^* \equiv \underset{u \in \mathbb{R}}{\partial} \left(\left\| G_i^p(u_i) - G_i^t(u_i) \right\| \right) \Rightarrow \min.$$

The objectives are to minimize the error of each subsystem so that there are optimal solution results for each objective.

To solve the Pareto optimality of the hierarchy in a system, all the objective functions of the subsystems and the constraints are raised to the upper system with the vector of decision variables [16].

Method notation

Let S_n be a sub-system inherited from system $S \equiv \langle S_1, S_2, \ldots, S_n \rangle$, where the solution of the multi-objective optimization for each sub-system S_n:

$$S_n \equiv \begin{cases} \min/\max f_{nm}(x) & m = 1, 2, \ldots, M; \\ g_{nj}(x) \geq 0 & j = 1, 2, \ldots, J; \\ h_{nk}(x) = 0 & k = 1, 2, \ldots, K; \\ x_{ni}^L \leq x_{ni} \leq x_{ni}^U & i = 1, 2, \ldots, l; \end{cases}$$

and

$$F \equiv \left\langle f_{1m}(x), f_{2m}(x), \ldots, f_{nm}(x) \right\rangle$$
$$G \equiv \left\langle g_{1j}(x), g_{2j}(x), \ldots, g_{nj}(x) \right\rangle$$
$$H \equiv \left\langle h_{1k}(x), h_{2k}(x), \ldots, h_{nk}(x) \right\rangle$$
$$X_i^L \equiv lower < x_{1i}^L, x_{2i}^L, \ldots, x_{1i}^L >$$
$$X_i^U \equiv Upper < x_{1i}^U, x_{2i}^U, \ldots, x_{1i}^U >$$

for all the equations above will give us:

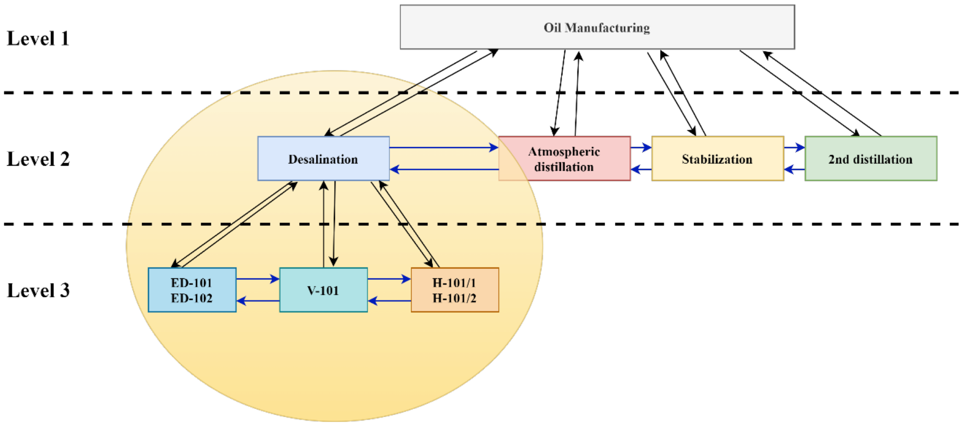

Fig. 1. Hierarchical Pareto communication structure

$$S \equiv \begin{cases} \min/\max F_m(x) & m = 1, 2, \ldots, M; \\ G_j(x) \geq 0 & j = 1, 2, \ldots, J; \\ H_k(x) = 0 & k = 1, 2, \ldots, K; \\ X_{ni}^L \leq X_{ni} \leq X_{ni}^U & i = 1, 2, \ldots, l. \end{cases}$$

Each subsystem S_n is solved individually using standard Pareto optimization. Then, the results are transferred to the higher-level system so that each subsystem can be compared, resulting in the bounds of each objective being reduced to the subsystem. A lower level of the system (the subsystem) can be analyzed, and the knowledge gained can be applied to the upper subsystems. It is possible to optimize each subsystem individually, regardless of the complexity of the system, to find solutions for that subsystem. Integration of subsystems is done by synchronizing variables that are adjusted at a higher level to achieve the optimal solution for the system. Certain optimality requirements can be reduced at the lower level to obtain optimal solutions for certain subsystems, which can then be reapplied at the higher level to achieve subsystem equality. The important feature of hierarchical Pareto optimization is that it simplifies the complex systems by reducing the dimensionality of each subsystem so that an efficient mathematical framework can be created. It is possible to apply several optimization methods to find an optimal solution based on the structure of the system.

Hierarchical Pareto optimization is based on communication between levels. It starts with these steps:

- Determine the Pareto set at each lower level of the system based on their respective objectives.
- Update the solution and its parameters at the upper level.
- Cumulate the new solutions from all subsystems and compare it with the previous solutions to obtain the optimal parameters for the system.
- Return the parameters that give an optimal solution for the system (even if it is not the optimal solution for the subsystem).
- Repeat these steps until no more changes are possible.

Fig. 1 illustrates the communication process between levels, where the subsystem at level 2 (desalination plant) receives the Pareto set of its subsystem at level 3. Then it compares the results obtained from it with the previous results and these parameters are also updated at level 1, up to a certain criterion where there are no changes in the parameters used in the Pareto optimization algorithms. Fig. 2 describes the hierarchy of Pareto optimization algorithms.

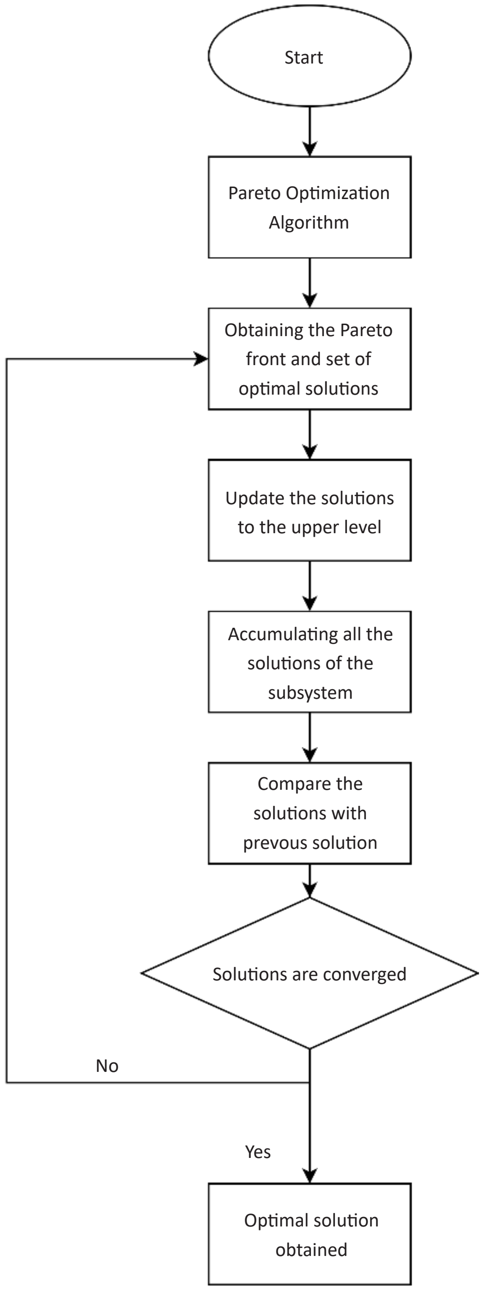

Fig. 2. Hierarchical Pareto optimization algorithm

Case of study and experimental results

Oil manufacturing

The oil manufacturing is composed of more than 100 components, which are:

- 2 compressors;
- 7 filters;
- 5 atmospheric columns;
- 14 tanks;
- 25 pumps;

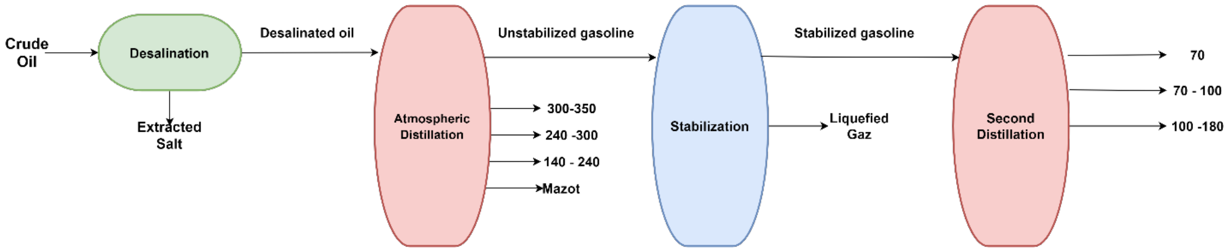

Fig. 3. Oil manufacturing structure

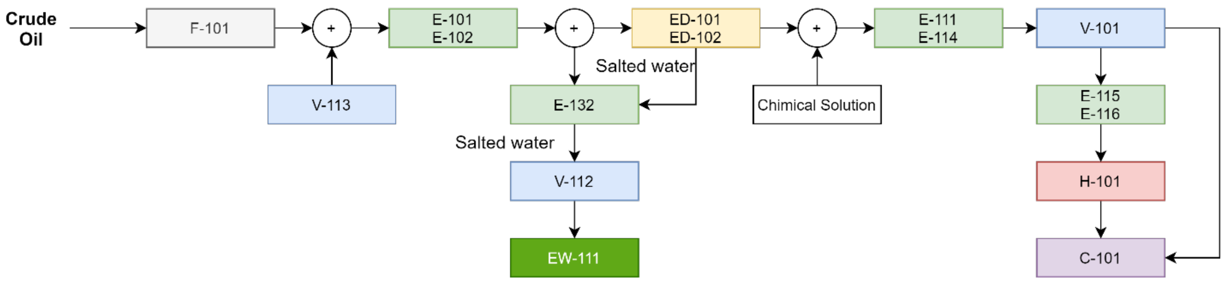

Fig. 4. Desalination structure

- 38 heat exchangers;
- 8 air coolers;
- 1 furnace;
- 10 refrigerators;
- 2 electric hydrators;
- and other reserve components.

Oil refining is divided into four main processes: Desalting Process, Atmospheric Column, Stabilization, and the 2nd Atmospheric Column (Fig. 3). Each of these systems consists of subsystems, each of which has its own control factors and objectives.

Most components, such as the filters, cannot be controlled. They filter the oil with a fixed property uncontrollable by the control system.

Fig. 4 shows the subsystems of desalination, but the major components are:

- ED-101, ED-102: the electro-dehydrator, which separates water and salt from the oil.
- V-101: the gas separator, which separates the gas from the liquid.
- H-101: the furnace that heats the oil and prepares it for the next process, atmospheric columns (represented by C-101 in Fig. 4).

Note that C-101 (the atmospheric column) is not part of the desalination process, but a process of the atmospheric column system.

Furthermore, the furnace in our study consists of two separate sections, namely H-101/1 and H-101/2.

From Table 1 you can see that all processes are controlled by temperature and pressure. Due to great influence of these factors on the manufacturing process, on the other hand, the goal of each process is determined by the quality and productivity of that process.

The quality of the process varies according to the process. In the case of the electric dehydrator (ED-101/ED-102), the quality depends on the percentage of water and salt extracted from the oil. The productivity of the process is the quantity of the production.

Table 1

Control factors and objective of each process

Process	Control factors	Objectives	
ED-101	Temperature	Quality	Productivity
	Pressure		
ED-102	Temperature	Quality	Productivity
	Pressure		
V-101	Temperature	Quality	Productivity
	Pressure		
H-101	Temperature	Quality	Productivity
	Pressure		

Method of analysis

As mentioned in the notation of the method, each process determines its local Pareto front, which is used in our hierarchical Pareto optimization. For this reason, we use the provided data as a learning phase to determine the approximation function of each process using a neural network.

Each model of these models is optimized using Bayesian hyperparameter optimization, since each process has its own neural network model.

Moreover, since the system is dynamic, the approximation function will change over time as the process continues to learn.

Fig. 5 shows the output of our neural network as a red line. This is the approximation function used as the optimized approximation function in our proposed approach.

Table 2

Comparison between the boundaries obtained from standard and hierarchical Pareto optimality

Process	Control factors	Standard optimality	Pareto	Hierarchical optimality	Pareto
		Lower	Upper	Lower	Upper
ED-101	Temperature	80	100	94.99	99
	Pressure	0.9	1.4	1.0761	1.12
ED-102	Temperature	80	100	96.28	99.83
	Pressure	0.9	1.4	1.0703	1.089
V-101	Temperature	110	130	128.62	129.61
	Pressure	0.1	0.3	0.143	0.1458
H-101/1	Temperature	700	820	746	748
	Pressure	0.9	1.75	1.40	1.53
H-101/2	Temperature	700	820	759	761.40
	Pressure	0.9	1.75	1.22	1.35

From the Table 2, notice that the boundaries of each process are smaller using the hierarchical Pareto optimality compared to a local Pareto optimality, which means the hierarchical Pareto optimality will give us a more precise result that the standard local Pareto optimality.

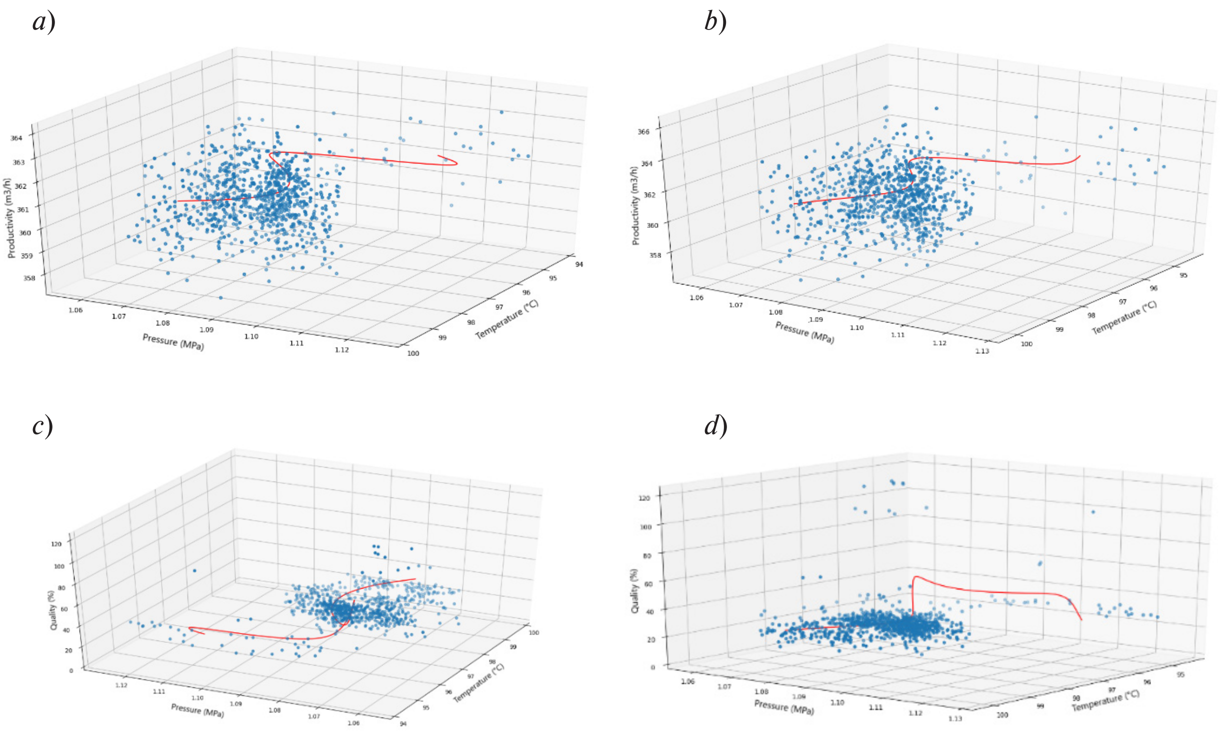

Fig. 5. ED-101/ED-102 temperature and pressure induced changes in productivity and quality

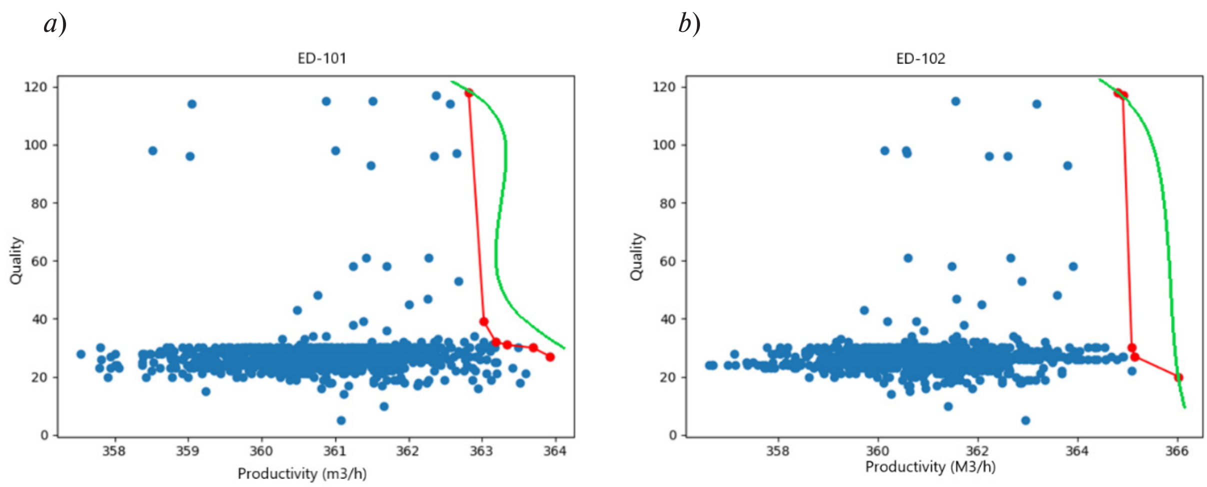

Fig. 6. Pareto front of the electro dehydrator (ED-101/ED-102)

Fig. 5 illustrates the changes in productivity and quality caused by the temperature and pressure in electro dehydrator (ED-101/ED-102). The red line demonstrates the approximated function of the processes. Depending on the approximated function, we can set the boundaries of a standard process using the local Pareto optimality as showed in Table 2.

Table 3 shows the Pareto optimality hierarchy results obtained by each of the configurations of the Pareto optimality hierarchy shown in Fig. 4.

Table 3

Pareto front of the electro dehydrator process (ED-101/ED-102)

ED-101			ED-102		
Pareto front	Temperature, °C	Pressure, MPa	Pareto front	Temperature, °C	Pressure, MPa
1	96.0093078613281	1.06980288028717	1	96.2793731689453	1.07028067111968
2	97.3932571411133	1.07608544826508	2	96.2870025634766	1.07076907157898
3	99.00830078125	1.09186339378357	3	99.8252563476563	1.08780181407928
4	97.1836853027344	1.07648158073425	4	97.4791946411133	1.08474445343018
5	94.9846267700195	1.11944007873535	5	96.9774322509766	1.08872640132904
6	97.7228775024414	1.09258782863617			

In Fig. 6, the red line represents the Pareto set of each process, the green line is the obtained Pareto front, and the blue dots are possible configurations for these processes.

From Tables 2 and 3, you can see that these configurations are in the range of the optimal configuration, depending on the real data used for this experiment. They are clearly better too: the results gave us a smaller bandwidth of configuration data, and minimal bandwidth means better results.

Conclusion

In this paper, we illustrated the hierarchical Pareto optimality approach in an oil manufacturing for an intelligent control system and compared its results with a standard Pareto optimality. The reason is that for each process, all processes must be optimal, not just the main process. For example, the electric dehydrator removes water and salt in the range of 2 to 4 % (sometimes above 4 %). However, our research shows that maximum extraction is not always good, because sometimes a lower extraction is needed for the next process, depending on the crude oil (if it contains a high percentage of water and salt). This research is part of a larger research project where an agent uses Deep Reinforcement Learning to adapt the process and each agent uses the hierarchy of Pareto optimality to obtain the optimal configuration. Since this research has been applied to oil production, it can be extended to other fields.

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