THE PROCESS CONTROL ORIENTED TO MANUFACTURING QUALITY IN CONTINUOUS FLOW PROCESS

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This research focus on the need for making the process control (PC) more intelligent in the latency time, and an Augmented Lagrange Coordination (ALC) based collaborative optimization modelling is pro-posed to handle the online quality PC. The ALC, an emerging variable granularity model, is introduced to coupling the subsystem with Taguchi Method. As a distributed solution, it offers an approach of general horizontal and vertical collaboration method to allocate the quality deviation into each granularity and configured node. A case study based on Series Solar Cell Production Line demonstrates the application scenario to illustrate the mechanism of ALC.

Keywords: Quality Control; ALC; Manufacturing Service Allocation.

1. Introduction

With the widespread of the Internet of Things, the operation paradigms of manufacturers has changed a lot. The MSA bears the trace of the existing manufacturing modes[1]. In the MSA, the data-driven target-oriented PC is a hotspot and draws the sight of the world, which can be regard as an encapsulated manufacturing service to match the diversiform operation demands. In some researches, the service or the demand is time, or cost [2], or assembly accuracy[3], the control ability of process parameters[4], or something else. To fulfil the personalized task, the PC plays a crucial role in the operation. Effective and efficient PC can avoid both over provisioning and idle resource for achieving sustainable productions.

Abundant researches have been carried out on the PC[5]. The existing approaches can be classified into three types: the Automatic Process Control (APC)[6], Statistical Process Control (SPC), and Robust Parameters Design (RPD). The APC needs to carry out the calculus of the process, and then implement the compensation according to the model prediction. The basis of the APC is the calculus and the premise of SPC adaptation is the probability distribution, which

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means that the nonlinear system is not suitable for both of the approaches. The RPD based on Taguchi method or Advanced Taguchi Method can handle the challenges mentioned above. The online monitoring/controlling, and noise reduction & elimination are the two characteristics of the RPD, which is applied in this study.

While in the real world, the PC concerns more about the coordination of many kinds of parameters rather than a single signal[7]. Based on the pre-work[8], a slice of challenges still hinders the collaboration optimization in the PC:

(1) The horizontal and vertical coordination collaboration. The pre-research assumptions are harsh and limited into the following situations: ①Only horizontal collaboration[9]. ②Upstream processes oriented vertical single stage collaboration. The global optimal in the decision-making are restricted by these constraints. Totally speaking, there are no solutions for the general horizontal and vertical coordination collaboration in PC.

(2) Complex Coupling Function: Another limitation of recent researches is the dimensionless coupling between the subsystems and systems. The coupling function (between the subsystem to subsystem, and subsystem to system) is the foundation and premise of quantitation and calculation in the PC.

This study tries to apply the collaborative optimization method into the PC. The concept of collaborative optimization came from the Multidisciplinary design optimization (MDO), and are used to deal with the conflicts between different characteristics, such as time and cost, assembly accuracy and assembly rate [10], or some control signals. The well-known methods are Concurrent subspace optimization (CSSO) [11], Bi-level integrated system synthesis (BLISS) [12], Analytical target cascading, (ATC) [13] and Augmented Lagrangian Coordination (ALC) [11]. Among them, the CSSO and BLISS are two-layer architectures, a large number of system optimization analysis are needed before each partition, which will generate huge computational complexity. Moreover, its abilities on robustness and generalization are quite dreadful for the researchers. The ATC mainly uses to solve decentralized problem[15] and pays more attention to the cooperative control between different sublevels[14]. When construct the system objective function, it takes the system decision parameters and the independent decision subsystem parameters into account. It has a prominent advantage in solving multi-layer, flexible generalization, centralization and decentralization problems. After years research, it has achieved remarkable results and has been widely applied in Automobile manufacturing [11] and Aviation logistics Industry.

The primary aim of this research is to investigate how the ALC is extended to PC by using the RPD. This paper forms a collaborative optimization method, which can actively push control-oriented configuration according to the target and multi-level service constraints in reasonable latency time[14]. The general horizontal and vertical collaboration and calculable coupling function are proposed. The rest of the paper is organized as follows: In second section, the PC problem in continuous flow process and its characteristic are described in details. The third section presents the ALC in mechanism and method. The fourth section shows the architecture and function of the ALC in the PC. The fifth section takes the PC in Series Solar Cell Production Line (SSCPL) as an example to analyses the operation mechanism. And the last section concludes the paper and considers the future work.

2. Problem Description

Section 2 describes the problem itself in a general way, and argue for its characteristic.

In complex manufacturing systems, the PC is often responded by multiple control nodes[16]. Quite a few of these nodes are independent of each other and some are interact, which constitutes the complexity of PC [17]. In the continuous flow process, the ACP is used to control the single signal and the SPC is adopted to handle the control between signals with logical relationship. For better illustration, a geometric programming problem has been taken by using the PU control with SPC in the sterilization process of a beer canning production system as Equation 1:

$$PU(t,T) = t \times 10^{\frac{1}{z}\times(T-T_{ref})} \tag{1}$$

For better understanding, some notations are as follows:

Table 1

Some Notations of Equation 1

symbol	Notations
PU	PU cumulative effect
t	Holding time
T	Holding temperature
z	The coefficient of bottle type
T_{ref}	Effective starting temperature

While in the complex system, there is no mathematical formula for thousands of control nodes. Take the SSCPL as an example, shown in Fig. 1, this paper try to coupling the relationship between the processing quality and the control nodes (Such as the welding time, temperature, cutting time, etc.). Moreover, optimal control parameters will be found by inversely solving the coupling function.

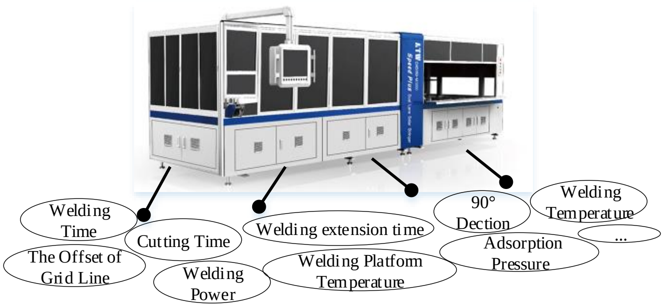

Fig. 1 The SSCPL and some control nodes

3. Methodology

Section 3 devoted to the basic aspects of the ALC. It is a decomposition-based and convergent collaborative optimization method[15]. Its primary thought is to allow each sub-decision-making-unit to make decisions independently and obtain global optimum through system partition and distributed decision-making system.

3.1. Centralized ALC

Tosserams and Nie [15] applied ALC to the dynamic optimal allocation of cluster supply chain. Their research models can be divided into centralized ALC and distributed ALC. In this paper, the centralized ALC is used as Fig. 2.

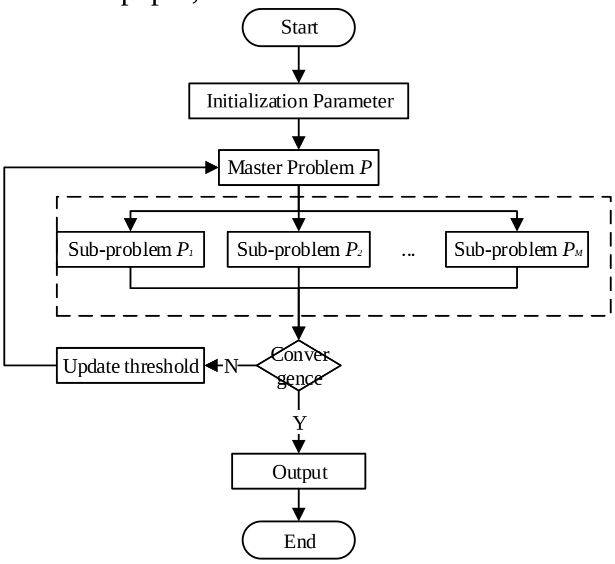

Fig. 2 Centralized ALC coordination method.

Its objective function and constraints of ALC are shown in Equation 2:

$$
\begin{aligned}
&[f_0(y, x_1, \dots, x_m) + \sum_{j=1}^{M} f_j\big(y, x_j\big)]_{min(z=[y^T, x_1^T, \dots, x_M^T])} \\
&s.t. \quad g_0(y, x_1, \dots, x_m) \le 0; \\
&\qquad h_0(y, x_1, \dots, x_m) = 0; \\
&\qquad g_i\big(y, x_j\big) \le 0, \quad j = 1, \dots, M; \\
&\qquad h_i(y, x_j) = 0, \quad j = 1, \dots, M;
\end{aligned}
\tag{2}
$$

The objective function contains coupling objective function $f_0: R^n \to R$ and Local objective function $\sum_{j=1}^{M} f_j(y, x_j)$. The Local objective function contains system and subsystem objective function.

The decision variable is $z = [y^T, x_1^T, \ldots, x_M^T] \in R^n$, consisting of a series of continuous variables $y \in R^n$ and local variables $x_j \in R^{n_j^x}$. The variables are only related to subsystem j.

The coupling constraint are $g_0: R^n \to R^{m_0^g}$ and $h_0: R^n \to R^{m_0^h}$. They are all non-separable. The local objective function are$f_h: R^{n_j} \to R$, and local constraints are $g_j: R^{n_j} \to R^{m_j^g}$, $h_j: R^{n_j} \to R^{m_j^h}$.

Based on this, a Lagrangian objective function are built as Equation 3:

$$L(f(oj), f(s.t.), \tau) = f(oj) - \tau f(s.t.) \tag{3}$$

Where f(oj) is the objective function, $f(s.t.)$ stands for the constraint function, and τ describes the Lagrangian multiplier, indicating the relaxation of the constraint. The problem solving of Equation 2 can be transformed into an extreme-value problem.

3.2. Auxiliary variables and consistency constraints.

The auxiliary variable $y \in R^{n^y}$ is introduced into each subsystem to separate the local variables g_i and h_i. Define the consistency constraints c and the set of c_{jn} is the consistency between sub-problem j and its neighbour$n \in N_j$ (in Equation 4):

$$c_{jn} = y_j - y_n = 0,\ \{n \in N_j | n > j\},\ j = 1, \ldots, M \tag{4}$$

Where N_j is the number of sub-problem j. The $n > j$ensures that only one of the linearly related c_{jn} and c_{nj} is in the consistency constraint.

3.3 Constrained relaxation

Define the slack variables (SV) $q = [c, g_0 + x_0, h_o]$, $x_0 > 0$ to transfer the inequality (The constraints in Equation 2) into an equation. Use the Lagrangian penalty function to relax the constraint q as in Equation 5:

$$\varphi(q) = v^T q + \|w \cdot q\|^2 \tag{5}$$

Where: v and w are the appropriate penalty parameter vectors, and the "·" denotes the matrix multiplication.

4. The proposed ALC for the process control in SSCPL

Section 4 demonstrates the implementation of the ALC in the PC on SSCPL.

4.1 Description of Model in SSCPL

As shown in Fig. 3, there are 4 levels in the SSPLC (System-Level, Unit-Level, Characteristic-Level and Feature-Level). The operation modes of SSPLC are divided into horizontal cooperation and vertical constraint. The Warehousing, Slicing, Welding, Assembly and AGV belong to horizontal relationship. Fragmentation Characteristic (FC), Incline Characteristic (IC), Insufficient solder Characteristic (ISC) and Spacing Characteristic (SC) are vertical constraints of Series Welding Unit. The aim of this paper is to allocate the quality control node to improve the quality level of welding process. The first and foremost, according to the operation mode, the quality deviation should be allocated to each model node based on system level, unit level, characteristic level and feature level. According to the relationship between production and operation, a general explanation can be made in Table 2.

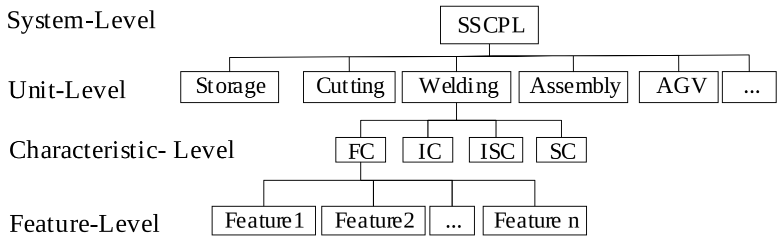

Fig. 3 Operation modes of SSPLC.

Table 2

General explanation of operational constraints

No.	Hypothetical condition	Universal Interpretation
1	If Quality loss ≥ξ, Unqualified.	ξ is the quality deviation threshold, including feature level, characteristic level, unit level and system level. The welding quality is abnormal immediately after exceeding the threshold.
2	The PC sequence is from top to bottom.	If the welding unit need reset the parameters, the quality control begins from the characteristic level to the feature level.
3	Only follow-up process parameters can be controlled.	According to the production process, the pre-process locks, and the change of parameters can only have effects on the subsequent process.
4	No response time delay for parameter setting.	After changing the parameters, the equipment will respond the changes immediately, and there is no response time delay.
5	Current quality level is independent with horizontal relation partners	Taking FC as an example, when the level is 2, the constraint is only applicable to the calculation of FC, not applicable to the IC, ISC and SC, nor to the constraint of overall series welding quality or system-level processing quality neither.

4.2 Description of ALC-based PC

As shown in Figure 3, the PC system is built into a distributed decision system, allowing each subsystem to enjoy the ability to make decisions autonomously, through auxiliary variables (y_j) and consistency constraints c_{jn}. Establish the coupling relationship between the subsystems, including the coupling variable (y) and the coupling function (f_0). After that, build up the subsystem quality constraint (g_j, h_j), and establish the local objective function of the subsystem (f_j). Finally, the quality-oriented system-level / unit-level / Characteristic-level PC model can be obtained as shown in Equation 6.

$$\sum_{i=1}^{M}\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 \quad min$$
$$s.t. \quad \begin{aligned} &\xi_L^x < g(i) = x_i < \xi_U^x; \\ &\xi_L^c < q(i) = \left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 < \xi_U^c; \\ &\xi_L < p(k) = \sum_{k=1}^{N} \lambda_k L(y_k) < \xi_U. \end{aligned} \tag{6}$$

The Lagrangian objective function of the model shows in Equation 7:

$$L = \sum_{i=1}^{M}\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 - \tau \sum_{j=1}^{P}\sum_{k=1}^{N} \lambda_k L(y_k) \tag{7}$$

Where x_i represents the decision variable. The ξ_L^x, ξ_U^x are the boundaries of the decision variables. The i denotes the number of the decision variable, and the range is [1, M].

The $\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2$ indicates the target value of the quality loss of decision variable (Taguchi Method, detail in the article paper[4]), the T_U^i, T_L^i represent the boundaries, the ξ_L^c, ξ_U^c are the boundary of the characteristic-level quality loss. The Equation 7 sketches the coupling constraint from Feature-Level to Characteristic.

The $\xi_L^x < g(i) = x_i < \xi_U^x$ sketches the coupling constraints based on signal to noise ratio from Characteristic-Level to Unit-Level, and Unit-Level to System-Level. The λ_k is the weight of quality feature y_k, the $L(y_k)$ stands for the loss function of Characteristic or Unit. The k means the number of decision variables in the coupling function and the range are in [1, N], N<M. In addition, the j is the number of feature, and its range is [1, P].

5 Case study

5.1 The Subsystem Objective function

Taking the welding unit as an example, the model shows in Equation 8:

$$\sum_{1}^{309}\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 \quad min$$
$$s.t. \quad \begin{aligned} &\xi_L^x < g(i) = x_i < \xi_U^x; \\ &\xi_L^c < q(i) = \left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 < \xi_U^c; \\ &\xi_L < p(k) = \sum_{k=1}^{N} \lambda_k L(y_k) < \xi_U. \end{aligned} \tag{8}$$

Its Lagrangian objective function is shown in Equation 9. In Equation 9, the x_i is the decision variables that can be acquired in the welding unit. The i means the number of the decision variable, [1, 309]. The $\sum_{k=1}^{11} \lambda^1{}_k L(y^1{}_k)$ indicates the coupling constraints of FC. The $\lambda^1{}_k$ denotes the loss weight of decision features in FC. The decision features (or the) are:

[*The pressure of wind knife,*
The adsorption of negative pressure of supplementary feeding system,
The adsorption of negative pressure of walking beam,
The adsorption of negative pressure of CCD platform,
The adsorption of negative pressure of the robot,
The edge detection (left/right/up/down),
The angle detection, the rollover test of 180°]

$$L=\sum_{1}^{309}\left(\frac{x_i-T_i}{T_U^i-T_L^i}\right)^2-\tau_1\left[\sum_{k=1}^{11}\lambda^1{}_kL(y^1{}_k)\right]-\tau_2\left[\sum_{k=1}^{2}\lambda^2{}_kL(y^2{}_k)\right]-\tau_3\left[\sum_{k=1}^{3}\lambda^3{}_kL(y^3{}_k)\right]-\tau_4\left[\sum_{k=1}^{2}\lambda^4{}_kL(y^4{}_k)\right]-\tau_5\left[\sum_{k=1}^{11}\lambda^5{}_kL(y^5{}_k)\right]-\tau_6\left[\sum_{1}^{309}\left(\frac{x_i-T_i}{T_U^i-T_L^i}\right)^2\right]-\left[\sum_{i=1}^{309}\tau_{i+6}x_i\right] \tag{9}$$

The range of k is [1, 11]. And the $\lambda^1{}_k$ are as follows (the calculate detail can be seen in[4]): [0.0928, 0.081562, 0.065366, 0.066353, 0.113024, 0.077423, 0.079874, 0.08003, 0.08045, 0.078273, 0.184846].

The $\sum_{k=1}^{2}\lambda^2{}_kL(y^2{}_k)$ sketches the coupling constraints of IC, where:$\lambda^2{}_k$= [0.729458, 0.270542]. The $\lambda^2{}_k$ describes the loss weight of decision features in IC: [speed up time, speed down time], the range of k is [1, 2].

The $\sum_{k=1}^{3}\lambda^3{}_kL(y^3{}_k)$ stands for the coupling constraints of ISC, where:$\lambda^3{}_k$= [0.270898, 0.516728, 0.212375]. The $\lambda^3{}_k$ is the loss weight of decision features in ISC: [The lamp power of Line A/B, The welding time of Line A/B, Temperature of welding platform], the range of k is [1, 3].

The $\sum_{k=1}^{2}\lambda^4{}_kL(y^4{}_k)$ is the coupling constraints of SC, where: $\lambda^4{}_k$ = [0.801695, 0.198305]. The $\lambda^4{}_k$ is the loss weight of decision features in SC: [Adsorption of negative pressure of walking beam, The step distance]. The k range is [1, 2].

The $\sum_{k=1}^{11}\lambda^5{}_kL(y^5{}_k)$ sketches the coupling constraints of Welding Unit, where: $\lambda^5{}_k$ = [0.068353, 0.054895, 0.055438, 0.09268, 0.068113, 0.07005, 0.069848, 0.068768, 0.067762, 0.269976, 0.114117]. The$\lambda^5{}_k$ is the loss weight of decision features in Welding Unit. The decision features are:

[*The welding time of A/B production line (abbreviated to FU11),*
The adsorption of negative pressure of supplementary feeding system (FU1),
The adsorption of negative pressure of CCD platform (FU2),
The adsorption of negative pressure of the robot (FU3),
The adsorption of negative pressure of walking beam (FU4),
The angle detection (FU5),
The edge detection (left/right/up/down, FU6 / FU7 / FU8 / FU9 respectively),
The rollover test of 180 (FU10).]

The range of k is [1, 11].

In addition, j represents the number of coupling function in the system level, its range is [1, 5], as shown in above five Equations respectively. "[]" in Lagrange objective function represents that no relaxation have been made in the decision features

5.2 The system objective function

The core idea of solving the PC model is to construct the Lagrange Equation. The constraints of inequalities are as Equation 10:

$$\xi_L^x < g(i) = x_i < \xi_U^x; \tag{10}$$

The SV x_{i+309} and x_{i+618} are introduced. In order to guarantee the inequality, the quadratic is used. Then the original inequality constraints is rewritten into Equation 11:

$$\begin{gathered} g(i) = x_i - \xi_U^x + (x_{i+309})^2 = 0; \\ g(i+309) = x_i - \xi_L^x - (x_{i+618})^2 = 0; \end{gathered} \tag{11}$$

Similarly, the SVy_{i+309},y_{i+618}, $\xi_L^c < q(i) = (\frac{x_i - T_i}{T_U^i - T_L^i})^2 < \xi_U^c$ is introduced and transformed into Equation 12:

$$\begin{gathered} q(i) = (\frac{x_i - T_i}{T_U^i - T_L^i})^2 - \xi_U^c + (y_{i+309})^2 = 0; \\ q(i+309) = (\frac{x_i - T_i}{T_U^i - T_L^i})^2 - \xi_L^c - (y_{i+618})^2 = 0; \end{gathered} \tag{12}$$

The SV z_{i+5} , z_{i+10} , $\xi_L < p(k) = \sum_{k=1}^{N} \lambda_k L(y_k) < \xi_U$ is introduced and transformed into Equation 13.

$$\begin{gathered} p(i) = \sum_{k=1}^{N} \lambda_k L(y_k) - \xi_U + (z_{i+5})^2 = 0; \\ p(i+5) = \sum_{k=1}^{N} \lambda_k L(y_k) - \xi_L - (z_{i+10})^2 = 0; \end{gathered} \tag{13}$$

Then the objective function of Lagrange function finally is rewritten from Equaion (8) to Equation 14. The cooperative optimization problem is transformed into the extremum problem of Equation 14. Conventional extremum problem is solved by partial differential computation of the Equation, and a set of equations with no less than the number of independent variables is constructed for the solution. For the extreme value problem of the Lagrange objective function, the threshold of the independent variable is in Equation 15.

There totally are 2801 dimensions, as shown in Equation 15, and the solution need to construct at least 2801 differential equations, which leads a high complex calculation. Therefore, the Genetic Algorithm (GA) is adopted. The GA codes each SV and the all the Parents whose L in Equation 14 fall in the range of certain grade are retained.

$$\begin{aligned}
L = &\sum_{i=1}^{309}\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 - \tau_1\left(\sum_{k=1}^{11}\{\lambda_k^1 L(y_k^1)\} - \xi_U + (z^1)^2\right) - \tau_2\left(\sum_{k=1}^{11}\{\lambda_k^1 L(y_k^1)\} - \xi_L - (z^2)^2\right) \\
&-\tau_3\left(\sum_{k=1}^{2}\{\lambda_k^2 L(y_k^2)\} - \xi_U + (z^3)^2\right) - \tau_4\left(\sum_{k=1}^{11}\{\lambda_k^2 L(y_k^2)\} - \xi_L - (z^4)^2\right) - \tau_5\left(\sum_{k=1}^{11}\{\lambda_k^3 L(y_k^3)\} - \xi_U + (z^5)^2\right) \\
&-\tau_6\left(\sum_{k=1}^{11}\{\lambda_k^3 L(y_k^3)\} - \xi_L - (z^6)^2\right) - \tau_7\left(\sum_{k=1}^{11}\{\lambda_k^4 L(y_k^4)\} - \xi_U + (z^7)^2\right) - \tau_8\left(\sum_{k=1}^{11}\{\lambda_k^4 L(y_k^4)\} - \xi_L - (z^8)^2\right) \quad (14) \\
&-\tau_9\left(\sum_{k=1}^{11}\{\lambda_k^5 L(y_k^5)\} - \xi_U + (z^9)^2\right) - \tau_{10}\left(\sum_{k=1}^{11}\{\lambda_k^5 L(y_k^5)\} - \xi_L - (z^{10})^2\right) \\
&-\sum_{i=1}^{309}\left\{\begin{aligned}&\tau_{i+10}\left[\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 - \xi_U^c + (y_i^1)^2\right] + \tau_{i+319}\left[\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2 - \xi_L^c - (y_i^2)^2\right] \\ &+\tau_{i+628}\left[x_i - \xi_U^x + (x_{i+309})^2\right] + \tau_{i+937}\left[x_i - \xi_L^x + (x_{i+618})^2\right]\end{aligned}\right\}
\end{aligned}$$

$$\psi = \begin{bmatrix} x_1, \ldots, x_{309}, \ldots x_{927}, z^1, \ldots, z^{10}, \\ y_1^1, \ldots, y_{309}^1, y_1^2, \ldots, y_{309}^2, \tau_1, \ldots, \tau_{1246} \end{bmatrix} \quad (15)$$

Table 3

Some Notations of Equation 14

symbol	Notations
x_i	the decision variables
i	the number of the decision variable
ξ_L^x, ξ_U^x	the boundaries of the decision variables
$\left(\frac{x_i - T_i}{T_U^i - T_L^i}\right)^2$	target value of the quality loss of decision variable
$L(y_k)$	the loss function of Characteristic or Unit
k	the number of the features. In FC, its range is [1, 11]. In IC, it is [1, 2]. In ISC, it is [1, 3] and In SC, it is [1, 2].
${\lambda^1}_k$, ${\lambda^2}_k$, ${\lambda^3}_k$, ${\lambda^4}_k$	the loss weight of decision features in FC, IC, ISC and SC
SVx_{i+309} , SVy_{i+309} and SV z_{i+5}	the slack variables

5.3 Result Analysis

In this case, a cell that has not yet been full processed is studied. The initial welding grade is predicted to be level five (quality loss is 0.117). Due to demand, this cell need to upgrade to level three, and the quality loss constraint is (0.0472944, 0.0709416]. The quality loss standard can get in Ref. [4].

The Lagrange function *L* needs change from 0.117 into (0.0472944, 0.0709416]. After the calculation of GA, this research gets the acceptable decision variables as shown in Table 4.

The initial population is depending on the current production signal range. The crossover and mutation probability is 0.97 and 0.03 respectively, and the iteration stopping condition is set to 200 generations. The running time is few seconds (Matlab R2011b, 2.2GHz and 12G RAM). As shown in Table 4, the initial processing parameters of the selected cell are as the first column and the PC after the ALC is the second. Combined with the process accuracy, the parameters are finally configured as the third column and the quality loss level is three. For better illustration, this paper takes the FU11 (Welding time of A/B production line) as example. In the process, the welding time of the system was 2600ms. After the ALC & GA, the FU11 is 2001ms. The quality loss of Welding Unit-Level (WUQL) falls in to (0.0472944, 0.0709416]. While according the Welding time control accuracy, the welding time finally is set as 2000ms, and the WUQL is 0.5142.

Table 4

The parameters before and after PC

	Before	After	Setting
Quality Loss	Level 5		Level 3
FU1	-50	-42.21	-42.2
FU2	-19.4	-19	-19
FU3	-67.5	-67.21	-67.2
FU4	-48	-39.05	-39
FU5	10	10	10
FU6	42	39.06	39
FU7	45	44.08	44
FU8	35	42.06	42
FU9	44	39.92	40
FU10	20	17	17
FU11	2660	2001	2000
WUQL	0.11717	0.0502	0.05142

5.4 Discussion

Results indicate that ten of eleven parameters changed in the case study. This paper try to discuss wheatear the solution with less than ten is better or not. Considering the cost of controlling and the complexity of the operation, the less parameters that changed in the ALC, the better the solution is. Based on this theory, only one parameter that changed in the ALC is the best.

While this paper harbour the idea that, with the WUQL constrained to the (0.0472944, 0.0709416], ten parameters with slight fluctuations is better than one parameters with large fluctuations. Just take the case study as an example. Ten parameters with slight fluctuations is shown in the Table 4. If change only one parameter, the FU11 needed to be set up to 9700ms. The takt time has been influenced a lot. What's more, in Table 2, some Hypothetical conditions are made to simply the model. Such as No.4: No response time delay for parameter setting. While in actually, especially with huge fluctuations, the delay of response time can not be ignored. Consequently generally speaking, the solution with ten slight fluctuations is better than the one with large fluctuations.

6. Conclusion

In the PC, a multi-level quality coupling function of ALC is constructed. Constraint relaxation is carried out by using auxiliary variables and consistency constraints. Dimensionless coupling of multi-level is realized. The ALC & GA builds a general horizontal and vertical collaboration coupling function, provides a wide open-structure for the response mechanism of dynamic cooperation.

The paper tries to investigate how the ALC is extended to PC by using the RPD and form a collaborative optimization method, which can actively push control-oriented configuration according to the target and multi-level service constraints in reasonable latency time. In this work, the effectiveness and efficiency of the algorithm are verified by a case study.

The future work may follow several aspects:

In this paper, "the Target is best" (in Taguchi Method) are adopted into the calculation. In the future, "The lager is better" and "The smaller is the better" are going to be taken into consideration.

The PC is based on the locked structure of the product line. The future work try to examine the application of ALC in variable granularity production system.

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