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A Statistical Solution to Mitigate Functional Requirements Coupling Generated from Process (Manufacturing) Variables Integration-Part 2: A Case Study on Clarifying the Effect of Process (Manufacturing) Variables Integration on Functional Requirements Independency

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Abstract

In this part of the work, to illustrate the strength of the "partial and semipartial correlation analysis, as the proposed solution described in detail in part 1, we consider design problem of the manufacturing system of a given product based on a set of hypothetical data and show how to explore the most appropriate integration choices in which the (causal) dependencies of the concerned PVs are minimal. Based on the results of this study, we emphasize that incorporating the identified sensitive PVs into the integration process will eventually lead to coupling among a subset of the product's FRs and isolation of these PVs is recommended as an ideal solution. However, sometimes, in the real world, for some of logical and/or technical reasons; such an ideal solution might be impossible. To deal with such a dichotomy, we use the Design of Experiments (DOE) methodology and offer the idea of controlling the values of the concerned PVs at specific levels to find the most appropriate condition (s) under which the minimal (causal) correlation between the integrated PVs may be achievable. On the basis of this idea, the worthwhile information the manufacturing system designers require to detect the safe levels at which the PVs can be integrated is achievable.

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*Keywords:*Independence Axiom; Noise Factors; Process (Manufacturing) Variables Integration; Partial & Semi-partial Correlation Analysis; Design of Experiments (DOE) Methodology

1. Introduction

In order to successfully satisfy customers of a product and retain their loyalty, "Quality" of the product is crucial [1]. For this reason, today, in competitive production industries, it is important to provide the customers with "high quality" products at "minimal production Costs" [2-3]. Concerning minimizing the product development costs, among all of potential factors that can significantly increase the production costs, effect of incapable manufacturing systems is considerable [3]. In fact, since an unhealthy manufacturing system with different kinds of vulnerabilities may cause quality degradation for the product through making a series of considerable variations in the product's specifications, design of a sound manufacturing system may considerably pave the way for reaching a high quality product [4-8].

From the Axiomatic Design (AD) theory, a manufacturing system is, in fact, an engineering system intended to support the product's PVs [9-12]. Therefore, from this view, any technical problem for supporting the PVs is considered a serious obstacle for satisfying both DPs and FRs of the product. That is, design of a capable manufacturing system should be regarded as one of the most critical steps in developing a high quality product [12-13].

With respect to design of a sound manufacturing system based on the principles of the AD theory, part 1 of this work proved that integration of the product's PVs on a single process entity is a good way for reaching system designs with relatively lower complexity provided that no serious "noise

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factors" exist in the system [14]. In fact, in part 1 of this study, we argued that, due to the presence of some active noise factors in manufacturing environments, the integration of PVs may unintentionally result in development of some significant statistical causal relationships among a specific subset of the PVs. Part 1 of this work showed that any statistical causal relationships among the PVs results in violating the AD's First (Independence) Axiom in both process and physical design of the product even though uncoupled or decoupled mapping designs are apparently presented and increases the cost (loss) the product's customers have to incur. However, because of some technical/ physical/financial constraints, we often have to integrate the PVs.

In part 2 of the present work, the application of the proposed statistical solution, built on partial & semi-partial correlation analysis, using a case-study is illustrated. In fact, in this part of this study, we are going to employ the proposed solution, described in detail in section 4 of part 1 of this work study, to study design problem of the manufacturing system of a product with the aim of exploring the most appropriate integration choices in which the PVs dependencies are minimal is illustrated. In this case- study, we have used a set of hypothetical data to illustrate the application of the proposed solution.

2. Case Study: Analysis of the Process Integration Effect on Independency of Functional Requirements of a Product

In this section of part 2, for the purpose of illustrating effect of the process integration practice on independency of Functional Requirements (FRs) of a product, consider a manufacturing system of a given product about which "poor Return of Investment (ROI)" has been reported as major concern of the management. On the basis of the information elicited from a series of interviews with the stakeholders, it is concluded that such an undesirable event is originating from "low product variety". Because of this, with the aim of dealing with the problem effectively, at the first (highest) level of the system abstraction, "improvement of the ROI" is defined as one of the most important FRs that must be established at the functional domain of the product. Moreover, in order to satisfy this FR, a "production system with high level of variety" is needed as the respective Design Parameter (DP) at the physical domain of the product. Finally, for the purpose of fulfilling this DP, a Flexible Manufacturing System (FMS), as the corresponding PV at process domain of the product, is developed.

With respect to developing an effective FMS, for the particular purpose of the present study, here we are going to concentrate our considerations just on this design variable (FMS) and continue the work by confining our discussion into decomposing this PV into a set of sub-PVs at the second level of hierarchy. Hence, followings are given as the PVs that must be established at the second level of system abstraction;

- $PV_{.1}$: Flexible Trained Manpower
- $PV_{.2}$: Flexible Material Handling via CNC Machines
- $PV_{.3}$: Standardized Procedures

At this level of decomposition, a multi-skill worker, as a flexible trained manpower, is employed to apply the standardized procedures and commonly work with two different CNC machines. In fact, at the current level of decomposition, for some economical and technical reasons, integration of Man, Machine, Method, and Material is inevitable. Concerning this kind of process integration, it should be noted that such a process integration is, in fact, an "information integration". In this case, the interaction between "man" and "machine" can be regarded as one of the most important sources of generating "noise factors". Regarding this case, the number of settings the machines require to properly operate is emphasized as the most serious nose factor that should be mitigated if it cannot be eliminated completely. In fact, if the number of required settings for two machines significantly increases, the worker may not appropriately divide his/her available time between two machines and, as a result, the machines will not be served perfectly. In such a situation, the functions of the machines may depend causally on each other even though they are originally independent of each another. In other words, if increase in number of the settings exceeds a specific limit, the system will lose its flexibility to some extent and functions of the machines will be causally correlated with each other. However, as mentioned earlier, for some of technical reasons, this integration has to be done.

For the purpose of illustrating the strength of the proposed solution in detecting whether there is a (causal) correlation between a given pair of the concerned PVs, Table 1 is given to present ten hypothetical observations provided for each of the PVs (PV_1, PV_2, and PV_3).

Table 1. The PVs Observations

Iteration (Day)	$PV_{.1}$	$PV_{.2}$	$PV_{.3}$
1	68.00	72.00	74.00
2	46.00	55.00	61.00
3	50.00	56.00	51.00
4	43.00	48.00	45.00
5	76.00	54.00	60.00
6	59.00	46.00	62.00
7	40.00	52.00	35.00
8	36.00	43.00	38.00
9	40.00	58.00	46.00
10	53.00	56.00	49.00

Prior to applying the partial and semipartial correlation analysis, it is useful to first consider the "simple correlations" (zero-order correlation) between every pair of the PVs. Such a consideration can provide important general information about statistical tendency of the PVs to be correlated with each other (Table 2).

As can be seen in Table 2, it seems that the $PV_{.1}$ and the $PV_{.3}$ tend to be correlated with each other significantly. In addition, according to the argument presented in part 1 of the study, here it is necessary to emphasize that this statistical relationship, that has been developed between the $PV_{.1}$ and the $PV_{.3}$ unintentionally, implies a causal relationship between this pair of the PVs. That is, the inherent independence of the $PV_{.1}$ and the $PV_{.3}$ has been violated.

Table 2. The zero-order correlation among $PV_{.1}$, $PV_{.2}$, & $PV_{.3}$

		$PV_{.1}$	$PV_{.2}$	$PV_{.3}$
$PV_{.1}$	Pearson Correlation	1	.458	.791**
	Sig. (2-tailed)		.184	.006
	N	10	10	10
$PV_{.2}$	Pearson Correlation	.458	1	.603
	Sig. (2-tailed)	.184		.065
	N	10	10	10
$PV_{.3}$	Pearson Correlation	.791**	.603	1
	Sig. (2-tailed)	.006	.065	
	N	10	10	10

**. Correlation is significant at the 0.01 level (2-tailed).

However, in order to further examine the tendency of the three random variables $PV_{.1}$, $PV_{.2}$, and $PV_{.3}$ to be correlated with each other, performing a course of "partial and semi-partial correlation analyses" may be more informative. For this reason, the Table 3 is provided to give required information about the first-order partial correlation between $PV_{.1}$ and $PV_{.2}$ where the effect of $PV_{.3}$ is removed.

Table 3. The First-order Partial Correlation between $PV_{.1}$ and $PV_{.2}$ where the Effect of $PV_{.3}$ is removed.

Control Variables			$PV_{.1}$	$PV_{.2}$
$PV_{.3}$	$PV_{.1}$	Correlation	1.000	-.041
		Significance (2-tailed)	.	.917
		Df	0	7
	$PV_{.2}$	Correlation	-.041	1.000
		Significance (2-tailed)	.917	.
		Df	7	0

According to Table 3, in fitting an appropriate multiple regression model in which $PV_{.2}$ and $PV_{.3}$ are used as explanatory variables (regressors) to predict (control) behavior of the $PV_{.1}$, when the $PV_{.3}$ has already been in the model, adding the $PV_{.2}$ does not show any significant contribution to predicting (controlling) the behavior of the $PV_{.1}$. This fact, therefore, clearly implies that incorporating $PV_{.3}$ into the integration process which involves $PV_{.1}$ and $PV_{.2}$ should be prohibited. In other words, integrating $PV_{.1}$ and $PV_{.3}$ on a single process entity may result in developing a causal relationship between these two PVs and, hence, a "coupled process design" is expected to result. Continuing the "partial correlation analyses" for three process variables $PV_{.1}$, $PV_{.2}$, and $PV_{.3}$, the same results are obtained and existence of a causal relationship between $PV_{.1}$ and $PV_{.3}$ is confirmed. According to Table 4, in order to predict/control the behavior of the $PV_{.1}$, incorporating the $PV_{.3}$ into a regression model which already has included the $PV_{.2}$ is significantly effective.

Table 4. The First-order Partial Correlation between $PV_{.1}$ and $PV_{.3}$ where the Effect of $PV_{.2}$ is removed.

Control Variables			$PV_{.1}$	$PV_{.3}$
$PV_{.2}$	$PV_{.1}$	Correlation	1.000	.726
		Significance (2-tailed)	.	.027
		df	0	7
	$PV_{.3}$	Correlation	.726	1.000
		Significance (2-tailed)	.027	.
		df	7	0

That is, $PV_{.1}$ and $PV_{.2}$ can be considered to be independent of each other, but, on the other hand, since $PV_{.3}$ and $PV_{.1}$ are significantly correlated with each other, incorporation of the $PV_{.3}$ can significantly help us predict the $PV_{.1}$'s behavior soundly. Hence, in short, any choice of process integration which is to include both $PV_{.1}$ and $PV_{.3}$ should be rejected.

Similarly, analysis of information presented in the Table 5 also confirms that integrating the $PV_{.1}$ and the $PV_{.3}$ on a single process entity will result in a fully coupled system design as well;

Table 5. The First-order Partial Correlation between $PV_{.2}$ and $PV_{.3}$ where the Effect of $PV_{.1}$ is removed.

Control Variables			$PV_{.2}$	$PV_{.3}$
$PV_{.1}$	$PV_{.2}$	Correlation	1.000	.444
		Significance (2-tailed)	.	.231
		df	0	7
	$PV_{.3}$	Correlation	.444	1.000
		Significance (2-tailed)	.231	.
		df	7	0

The Fig. 1 outlines all information about degree of the PVs tendencies to be causally correlated with each other. As can be seen in this figure, significance of the first-order partial correlation between $PV_{.1}$ and $PV_{.3}$ where the effect of $PV_{.2}$ is removed is relatively considerable and, because of this fact, it specifically warns us about any choice of the PVs integration which involves both $PV_{.1}$ and $PV_{.3}$.

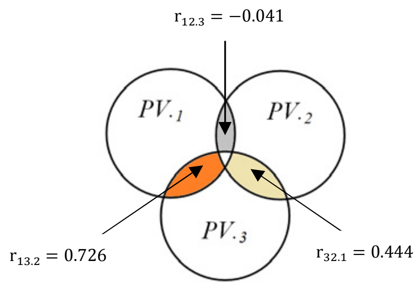

Fig. 1. The First-order Partial Correlation Analysis (Where; "1", "2", and "3" represent $PV_{.1}$, $PV_{.2}$, and $PV_{.3}$, respectively)

Although the partial correlation analysis has identified the best choice of the PVs integration well, here employment of the semipartial correlation analysis for ensuring existence of a specific statistical causal relationship between $PV_{.1}$ and $PV_{.3}$ where they are integrated on a single process entity can be insightful. For this purpose, calculating either $r_{2(1.3)}$ or $r_{2(3.1)}$ can serve the objective well. However, because of similarity, here we have confined ourselves to calculating $r_{2(1.3)}$. Hence, based on the Eq. (32) of part 1 of the study, Tables 6 and 7 are presented as followings;

Table 6. Coefficients of Determination from the Multiple Regression Model in which $PV_{.2}$ is Response Variable

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
A	.604a	.365	.184	7.21524

a. Predictors: (Constant), $PV_{.1}$, $PV_{.3}$

Table 7. Coefficients of Determination from the Simple Regression Model in which $PV_{.2}$ is Response Variable

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
B	.603[a]	.364	.285	6.75485

a. Predictors: (Constant), $PV_{.3}$

Therefore, based on the information given in recent two tables (Tables 6 & 7), the semipartial determination for measuring the marginal contribution of $PV_{.1}$ to predicting $PV_{.2}$ where $PV_{.3}$ is already included in the regression model is;

$$r^2_{2(1.3)} = R^2_{2.13} - R^2_{2.3} = 0.001 \quad (1)$$

Hence, on the basis of the semipartial correlation analysis, again, it is clearly concluded that any choice of process integration in which the $PV_{.1}$ and the $PV_{.3}$ are to be integrated together should be avoided.

Despite all conclusions above, however, it is clear that, logically, we cannot consider the workers ($PV_{.1}$) and procedures ($PV_{.3}$) to be two isolated variables. In fact, in the real world, obviously; we always have to integrate $PV_{.1}$ and $PV_{.1}$ together in order to accomplish any given production operation. This fact simply means that "integration of $PV_{.1}$ and $PV_{.3}$ is inevitable". Thus, it seems that here we are faced with a dichotomy.

To deal with such an intricate dichotomy mentioned above, controlling the values of the concerned PVs ($PV_{.1}$ and $PV_{.3}$) at specific levels, as an idea rooted in Design of Experiments (DOE) methodology, can help us find the most appropriate condition (s) under which the minimal (causal) correlation between the integrated PVs can be achieved. In other words, here use of the DOE methodology can help us explore that specific combination of the levels of the $PV_{.1}$ and the $PV_{.3}$ at which integration of these two PVs may not have serious (significant) effect on the FRs independency.

For the purpose of determining optimum conditions under which the safest process integration may be achievable, the (causal) covariance between the $PV_{.1}$ and the $PV_{.3}$ for every possible combination of the specified levels is calculated. The results of four replicants are shown as Table 8;

Table 8. Covariance between $PV_{.2}$ and $PV_{.2}$ Integrated Together in Different Combinations of the Specified Levels.

	Procedures					
Workers	15		70		125	
1	130	155	34	40	20	70
	74	180	80	75	82	58
2	150	188	136	122	25	70
	159	126	106	115	58	45
3	138	110	174	120	96	104
	168	160	150	139	82	160

In addition, on the basis of the information of the Table 8, results of complete analysis of variance (ANOVA) for the experiment can be presented as the Table 9.

Table 9. Results of Analysis of Variance (ANOVA) for the Covariance Data

Source	Sum of Square	d.f.	Mean of Square	F_0
Workers	10683.72	2	5341.86	7.91
Procedures	39118.72	2	19558.36	28.97
Interaction	9613.78	4	2403.44	3.56
Error	18230.75	27	675.21	
Total	77646.97	35		

Since $F_{0.05, 4, 27} = 2.73$, it is found that there are significant interactions between $PV_{.1}$ and $PV_{.3}$ at the 0.05 significance level. In addition, since $F_{0.05, 2, 27} = 3.35$, we can also find that the $PV_{.1}$ effects as well as the $PV_{.1}$ effects are significant at the 0.05 significance level as well. Moreover, to go one step further, since the interactions between $PV_{.1}$ and $PV_{.3}$ are significant, drawing graphs of means in each experimental combination can pave the way for exploring the specific combination in which the process integration of these two PVs may not lead to developing a significant causal relationship between them (Fig. 2). That is, we can find a specific condition in which process integration may not result in FRs coupling.

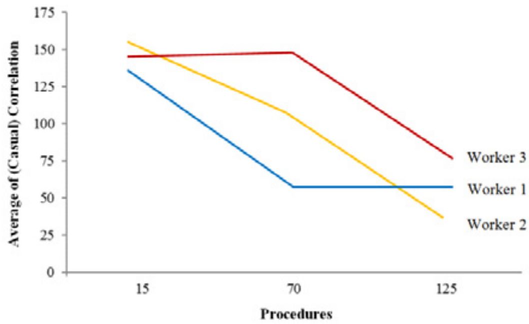

Fig. 2. Graphs of Procedures-Workers

Therefore, according to the Fig. 2; the minimal covariance (correlation) may be expected to experience in "Worker 1-Procedure 70" combination. To be clearer, in this combination of the $PV_{.1}$ and the $PV_{.3}$, we can be sure of maintaining independence of the $PV_{.1}$ and the $PV_{.3}$ while they are integrated together. In addition, it is recommended that "procedure 15 should be assigned to the worker 1" and "procedure 125 should also be assigned to worker 2" if we can tolerate some degree of coupling among the $PV_{.1}$ and the $PV_{.3}$.

3. Conclusion and Discussion

In this part of the study, for the purpose of illustrating the strength of the "partial and semipartial correlation analysis" as a sound statistical solution for finding the best choice of PVs integration and, hence, exploring the right way for reaching an optimal system design with minimal complexity, we considered the challenge of "the PVs independency maintenance in process integration practice" for a given manufacturing system of a product. On the basis of a set of hypothetical data, we showed that employment of "partial and semipartial correlation analysis" can effectively help system designers detect those PVs that strongly tend to be (causally) correlated with each other because of presence of some active noise factors in manufacturing environment. We emphasized that incorporating the identified sensitive PVs into the integration process will eventually lead to coupling among a subset of the product's FRs and, obviously; separation (isolation) of these PVs from each other is recommended as an ideal solution, if it is possible. However, in some of cases in the real world, logically and/or technically; such an ideal solution might be impossible. To deal with this dichotomy, we offered the idea of controlling the values of the PVs concerned at specific levels in order to find the best combination (s) of the specified levels in which the minimal (causal) correlation between the integrated PVs can be achieved. Concerning this idea, we employed the Design of Experiments (DOE) methodology to identify the specific condition in which the PVs integration may not have serious (significant) effect on the FRs independency. In fact, this approach provides useful information for the designers to identify the safe levels of the PVs at which PVs can be integrated and detect the risky levels at which the PVs integration will lead to a coupled system design.

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