Determining Cure Time of Rubber-Covered Mining Conveyor Belts using Multiresponse Surface Methodology

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Quality and productivity are two critical strategic operations competitive factors in modern manufacturing industry. A change in product quality standard specifications initiates related changes in the product manufacturing process design to ensure continued satisfaction of customer expectations. The specifications of the general-purpose rubber covered conveyor belt regional standard changed and customers had specific expectations they demanded on the quality of the product. Multi response surface methodology is used to determine the optimum cure times of rubber covered conveyor belts at the vulcanisation stage to ensure the product quality and process productivity requirements are met.

Keywords: Product Quality, Process Productivity, Multi-Response Surface Methodology, Screening Experiment, All Possible Regressions, Conformity of Response Surfaces

	Nomenclature
CCD	Central Composite Design
F_p	Number of fabric plies
F_t	Fabric thickness (mm)
MRSM	Multi response surface methodology
MSE	Mean squared error
MSPE	Mean squared prediction error
OLS	Ordinary least squares
PRESS Statistic	Predicted Residual Error Sum of Squares Statistic
R^2	Coefficient of determination
R^2 (adj.)	Adjusted coefficient of determination
R^2 (pred.)	Prediction coefficient of determination
RMSE	Root mean squared error
R_t	Rubber thickness (mm)
SADC	Southern African Development Community
T	Cure Temperature

1. Introduction

In this paper multi-response surface methodology (MRSM) was employed to approximate cure times for the vulcanisation stage of different thicknesses of rubber

covered mining conveyor belts to ensure that new product standard quality and productivity requirements were met.

The mining industry is at the heart of the SADC region's economic activities and development. Conveyor belts are critical for conveyance of bulk ore over distances and through various stages of processing. The regional product standard requirements for general purpose rubber covered conveyor belts for the mining industry had been amended at the insistence of customers seeking to lower operational costs through longer conveyor belting life. The minimum measured standard adhesion requirement between belting components had been increased from 5N/mm to 7N/mm. Good adhesion between conveyor belt components (covers and reinforcement fabric) ensures that they do not separate during heavy duty operations in the mines. The hardness of rubber compound covers is related to abrasion resistance which determines belting life by protecting the reinforcement fabrics. The separation of belting components during heavy duty operation and excessive rubber cover wear are the two major failures of conveyor belting during mining operations. Increasing adhesion between belting components and cover hardness ensures more belting life and therefore lowers mining operational costs. Key customers were insisting on a minimum of 10N/mm adhesion and a minimum cover hardness of 60⁰ Shore A. The company wanted to give its customers a minimum of 12N/mm adhesion. After experimentally determining the necessary changes in compound specifications, the optimum cure time of conveyor belts which would ensure a minimum of 12N/mm and 60⁰ Shore a hardness had to be determined for the vulcanisation stage. For manufacturers, optimum cure time is critical for product quality (satisfying customer requirements) and process productivity (minimum production time).

An MRSMS dataset was generated by first carrying out a screening experiment of assumed factors and then running an MRSMS designed experiment with the factors chosen for having significant effect on the quality parameters. Cure time and rubber thickness were chosen as the factors with significant effect on both response parameters. All possible regressions methodology was employed to come up with two sets of thirty-one models for each response from the MRSMS dataset. Conformity of response surfaces to expectations of adhesion and hardness response surface behaviour and shape was employed to trim the two sets of candidate models to four adhesion models and one hardness model. Data arrays of candidate adhesion response models were each overlaid with the data array of the single hardness model to determine four tables of cure time – rubber thickness pairings which were averaged and the result used to do a process validation run. The four adhesion and one hardness response models were assessed for fitness to the MRSMS dataset using mean squared error (MSE) and were assessed for prediction performance by computing leave-one-out and leave-two-out cross validations. Mean squared prediction error (MSPE) using data from the validation run was computed to confirm prediction accuracy. Finally, the results were compared with those from Stephen's rule, the most common method in use for estimating cure times for various rubber thicknesses.

Results confirm that the model with the best fitment to the MRSMS dataset is not necessarily the best in prediction capability. The average of the four sets of rubber

thickness to cure time results gave good prediction accuracy, as measured by MSPE, and showed better performance than the results from the method in common use (Stephen's rule). This shows that MRSM is quite efficient in estimating cure times given the total thickness of the rubber in the conveyor belt.

2. Literature Review

A number of techniques have been proposed in literature to estimate the cure time of rubber products such as nuclear magnetic resonance spectroscopy, differential scanning calorimetry, dynamic mechanical analysis, adaptive neuro-fuzzy inference systems, equivalent cure concept, and artificial neural networks (Gatos and Karger-Kocsis, 2004; Karaagacet al., 2011). In Gough (2017) the use of finite element analysis is considered and compared with Stephens' (1975) popular rule of thumb of adding 5 minutes to every $\frac{1}{4}$ of an inch of rubber thickness. Besides Stephens' rule of thumb, with only a cure meter, all the above methods could not be used as they require acquisition of specialised equipment. The general model for cure time in literature is given as:

$$\text{Cure Time} = \text{function of (type of the rubber, the curatives, vulcanization temperature)} + \text{error term} \quad (1)$$

Model (1) varies with compound specification (type of rubber and curatives) and assumes varying vulcanization temperature but does not account for the change due to rubber thickness because it assumes the use of the same standard test piece. Also, model (1) does not consider the case where there are different layers of constituent rubber compounds and other materials such as conveyor reinforcement fabric (nylon and/or polyester). The conveyor belting case required a multiple factor and response optimisation solution methodology.

Hejazi et al. (2017) state that multi response optimisation considers several inputs and outputs. Myers et al. (2016) define response surface methodology and that it is normally carried out in four distinct stages which are: (i) perform a statistically designed experiment, (ii) estimate the coefficients in the response surface equations (assumes use of parametric response surface models), (iii) check on the adequacy of the equations, and (iv) study the response surfaces in the region of interest. Myers et al. (2016) use examples of MRSM experiments that employ central composite designs (CCD), Box-Behnken, Orthogonal Arrays, and Plackett-Burman and other designs. CCD's have been very popular with MRSM practitioners because they are efficient, rotatable and near optimal. There is growing interest in optimal designs, especially D optimal, and computer-generated designs in MRSM (Khuri, 2017). The choice of experimental design is dependent on objectives of the study.

It is stressed by Khuri (2017) that the fitting of response models to MRSM datasets should be by means of multivariate techniques which consider correlations among the responses. Various parametric methodologies have been employed to estimate model parameters in MRSM such as seemingly unrelated regressions (Shah et al., 2004), ordinary least squares (OLS), shrinkage methodologies such as the LASSO and ridge regression and when the normality assumption does not hold, robust regression (Myers et al., 2016). Nonparametric methods, such as artificial neural networks (Noorossana et al. (2008), that are better in prediction but poor in

interpretation are now becoming common in MRSM literature. Modelling credibility of small sample size datasets is a common problem in statistics. Though most MRSM datasets fall into this category of small sample sizes, the problem is rarely discussed in RSM literature. In this work, the authors considered solution strategies that ensure credibility of small sample size modelling during MRSM work.

In accordance with Box and Youle (1955), statistical methods provide efficient tools for investigating a system whose general nature has been broadly decided. Myers et al. (2016) emphasize that optimisation should not be done prior to analysis of response surfaces. Response surface analysis ensures that the model's description of the process being investigated within the region of interest agrees with the behaviour of the 'true' process and thus ensures prediction accuracy. The authors divert from common MRSM practice of assuming that the best model fitting the MRSM dataset has a response surface that conforms to that of the data generating process and therefore relegating response surface analysis to the optimisation stage. The authors define response surface uncertainty as good fitness to MRSM dataset does not necessarily mean response surface conformity. Where prior process knowledge exists, the authors considered it prudent to use response surface conformity to select candidate models. The rheotrace of a rubber compound obtained from running a sample on a Rheometer gives the general cure-time characteristic of a rubber compound (See APPENDIX A). Rubber is a poor conductor of heat hence the cure time of a rubber sample is affected by its thickness. Therefore, a conforming response surface in this investigation is one that fulfils the general expected behaviour as suggested by the rubber compound rheotrace and the general cure time-thickness characteristic of rubber.

Response models for prediction should be assessed and ranked using prediction error rate which tests capability to predict new or out-of-MRSM-dataset data (James et al., 2013, Emmert-Streib and Dehmer, 2019). The training error rate underestimates prediction error rate by a measure of optimism because the model is designed to minimise fitted errors between it and the MRSM data points. Good fitness to the MRSM dataset can be indicated by classical model selection criteria such as R^2 , R^2 (adj.), and RMSE. Prediction model selection criteria include R^2 (pred.), PRESS and cross-validation. In the absence of a large dataset to use as an independent test set, Hawkins et al. (2003) recommends the use of cross-validation for small sample sizes. Classical model selection and prediction criteria, however, suffer from small sample size model selection criteria inefficiency (Seghouane and Bekara, 2004) and best choice disagreement (Schomaker and Heumann, 2018). The authors were of the opinion that a good model prediction capability assessment should deal with the problem of small sample size selection criteria inefficiency and should average or sum model rankings of different prediction criteria.

MRSM requires the simultaneous consideration of all predictive models at problem solution, within the region of process operability, because the response surfaces of different responses do not necessarily have similar form. It is usually assumed that MRSM responses are correlated within runs but independent otherwise (Mukhopadhyay and Khuri, 2010). Lindsay et al. (1960) proposed overlaying contours of response surfaces of models to determine the desired operating conditions for problems limited to two input variables. Approaches for optimisation

of two or more input variables in literature include the desirability function (Derringer and Suich, 1980), constrained optimization (Del Castillo and Montgomery, 1993), dual response (Myers and Carter, 1973), distance function (Khuri and Conlon), squared error loss (Pignatiello, 1993), proportion of conformance (Chiao and Hamada, 2001), Pareto fronts (Chapman et al., 2014a), posterior preference articulation (Lee and Park, 2016), fuzzy modelling and artificial neural networks (Şimşek, 2018). In the problem at hand the graphical method of Lindsay et al. (1960) best suited the two-input variable problem because of its simplicity and the ease to construct, analyse, and overlap three-dimensional response surfaces.

MRSM has been widely used in various fields of Industrial and Production Engineering being employed in the optimization of quality characteristics and in the optimisation of process parameters (Lee and Park, 2017; Deepack and Beedu, 2017; Hejazi et al., 2017; Şimşek, 2018). The contextual framework of MRSM as deduced from literature is given in APPENDIX B. The authors could not find where MRSM was specifically used to improve product quality and process productivity of the rubber covered conveyor belt vulcanizing process, especially to determine optimal cure times. MRSM was considered a suitable option in this work because of the non-availability of expensive equipment for determining cure times, the need to treat the case as a multiresponse optimisation problem, the possibility to avoid the use of classical model selection criteria and deal with the small sample size MRSM dataset modelling credibility problem.

The remainder of this paper is organised as follows. Section 3 presents the solution methodology combined with the results. Section 4 then presents the discussion. Section 5 presents the managerial implications whilst Section 6 presents the areas of future research. Section 7 gives the conclusion.

3. Solution Methodology

The maturity of the vulcanisation of constituent rubber compounds in conveyor belting is indicated by the adhesion of structural components to each other effected by the skim compound and the hardness of the cover compound. The vulcanisation stage of conveyor belting is done at a constant pressure and temperature. Using the experience available in the manufacturing entity a general model for the vulcanisation of rubber covered conveyor belting for specific cover and skim compounds was proposed as:

$$\text{Adhesion/Hardness} = \text{function of (cure time, rubber thickness, fabric thickness, number of plies) + error term} \quad (2)$$

The rubber thickness in model (2) is the sum of the skim and cover thicknesses. Unlike model (1), model 2 considers the existence of conveyor reinforcement fabrics. The intention of this study was to have a solution to model (2) using MRSM that gives a variant of model (1) of the form

$$\text{Cure Time} = \text{function of (rubber thickness, fabric thickness, number of plies) + error term} \quad (3)$$

3.1 The Theoretical Framework

The summary of the solution methodology is shown in Figure 1 below.

Figure 1 Shows the Schematic Summary of the MRSM Solution Methodology

The differences between the contextual MRSM framework from literature and the solution methodology employed are summarised in Table 1 below.

Table 1 Showing the Differences from the Contextual and the Theoretical Frameworks

	Difference	Justification
1	There was no distinct 'best' classical model selection stage. After all regressions modelling, response surface analysis was done to select candidate models with conforming response surfaces.	This was to avoid the 'best' model uncertainty and small sample size selection criteria inefficiency associated with classical model selection.
2	Fitness to MRSM dataset analysis (using MSE) and prediction capability assessment (using cross-validation) are performed separately.	Training MSE under estimates prediction accuracy of response models because of optimism bias.
3	Optimum results for all adhesion – hardness pairings which had conforming response surfaces were computed and averaged.	Avoidance of use of results from single model

3.2 Data Generation

This section covers the screening and MRSM experiments. In MRSM data is generated experimentally.

3.2.1 Screening Experiment

A 2_{IV}^{4-1} fractional factorial design experiment was run to select the factors that have significant effect on the quality and productivity parameters related to the rubber conveyor vulcanization process. The design was chosen because it only employs eight experimental runs to generate useful results. The four factors of equation (2) were used in the screening experiment. The factors were coded as: T = Cure time (min.); R_t = Rubber thickness (mm); F_t = Fabric thickness (mm); and F_p = Number of fabric plies. The factor levels in the screening experiment were set using process experience at hand. The experimental samples were randomised before the experimental runs were carried out. Three results of adhesion and cover hardness were measured, for each experimental run, and averaged in accordance with the requirements of the regional product standard. The averaged results are shown in Table 2.

Table 2 2_{IV}^{4-1} Screening Experiment Design with average Hardness and Adhesion Results

Run	T (min)	R _t (mm)	F _t (mm)	F _p	Ave. Hardness (°shore A)	Ave. Adhesion N/mm
1	17.5	5.9	0.7	2	52	10.01
2	25.5	5.9	0.7	6	59	11.89
3	17.5	10.1	0.7	6	55	5.40
4	25.5	10.1	0.7	2	58	10.90
5	17.5	5.9	1.8	6	52	8.98
6	25.5	5.9	1.8	2	59	12.00
7	17.5	10.1	1.8	2	55	7.30
8	25.5	10.1	1.8	6	58	10.44

The results were analysed using JMP 7 statistical software which isolated cure time and cover thickness as having significant effect on component adhesion and the °Shore A hardness of conveyor belting rubber covers. The effect of reinforcement fabric plies and thickness was insignificant. Equation (3) was, therefore, reduced to: Adhesion/Hardness = function of (cure time, rubber thickness) +error term (4)

3.2.2 MRSM Experiment

A two-factor CCD experiment with five centre points was employed to come up with the MRSM dataset. A design of this nature was favoured because of its efficiency, rotatability and its near optimal prediction variance. The five centre points were important for the determination of pure error. The experimental space was determined using process experience. Samples were randomised before the experimental runs were carried out and were cut and tested in accordance with the requirements of the regional rubber covered conveyor belting standard. Three results of adhesion and cover hardness were measured, for each experimental run, and

averaged in accordance with the requirements of the regional product standard. The average results are shown in Table 3 with specific information for each run. Columns T (min.) and R_t (mm) show cure time and total rubber thickness levels used in the experimental runs respectively.

Table 3 Averaged Results for the Two-Factor CCD MRSM Experiment

Run	T (min.)	R _t (mm)	Ave. Hardness (°shore A)	Ave. Adhesion(N/mm)
1	16	7.2	60	10.60
2	30	7.2	63	13.34
3	16	22.8	53	6.20
4	30	22.8	61	12.10
5	23	15	58	11.80
6	23	15	58	12.10
7	13	15	44	6.5
8	33	15	63	13.30
9	23	4	63	13.30
10	23	26	56	3.50
11	23	15	58	12.20
12	23	15	57	12.30
13	23	15	58	12.10

3.3 All Possible Regressions Modelling

Thirty-one (2⁵-1) OLS models were generated for each of the two responses by all possible regressions methodology from the MRSM dataset using Minitab 17. It was assumed that the second-degree model for both responses adequately approximated the behaviour of the true models within the region of interest. The belt curing model expands into the following second-degree parametric model

$$\text{Adhesion/Hardness} = \beta_0 + \beta_1 * T + \beta_2 * R_t + \beta_{12} * (T * R_t) + \beta_{11} * T^2 + \beta_{22} * R_t^2 + \text{error} \quad (5)$$

Where β_0 is the intercept and $\beta_1, \beta_2, \beta_{12}, \beta_{11},$ and β_{22} are estimates of parameters for cure time (T), and rubber thickness (R_t), the cure time by rubber thickness interaction term (T*R_t), and the second order terms (T²) and (R_t²), respectively. Rawlings et al. (1998) defined as small sample size anything satisfying the relationship $\frac{n}{k} < 40$ and that no model selection exercise should be taken seriously when the sample sizes are as small as $(n - k) \leq 10$, where n is sample size. In this case $\frac{n}{k} = \frac{13}{6} < 40$ and $(n - k) = (13 - 6) = 7 < 10$. This demanded rigour in the solution determining process for the credibility of results.

3.4 Response Surface Analysis

Response surfaces, contour diagrams and data arrays show the underlying behaviour

of response models in the region of interest. Candidate models for optimisation were chosen using response surface conformity. Response surfaces constructed using four different statistical analysis software were used to decide response surface conformity of response models to the vulcanisation process of rubber. The four statistical analysis software used are Microsoft Excel 10, JMP 7, Minitab 17, and Design Expert 7. Response surface analysis reduced adhesion candidate models from thirty-one to four and hardness candidate models to one. Table 4 shows the remaining four adhesion and one hardness models.

Table 4 Response Models with Conforming Response Surfaces

MODEL	β_0	β_1	β_2	β_{12}	β_{11}	β_{22}
T, R _t , T*R _t , T ² , R _t ² (Adhesion)	0.7400	0.8040	0.0970	0.0145	-0.0151	-0.0248
T, R _t , T*R _t , R _t ² (Adhesion)	8.6100	0.1070	0.0470	0.0145		-0.0231
T, R _t , T*R _t , T ² (Adhesion)	7.4000	0.6180	-0.6460	0.0145	-0.0111	
T, R _t , T*R _t (Adhesion)	12.9400	0.1070	-0.6460	0.0145		
T, R _t , T*R _t , T ² (Hardness)	29.1000	2.8400	-0.9180	0.0321	-0.061	

3.5 Analysis of Fitness to MRSM Dataset

The five models with conforming response surfaces (four adhesion and one hardness models) were assessed for fitness to the MRSM dataset using MSE. The formula for MSE is given below for a sample size *n*.

MSE= $\frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n}$, where *Y_i* is the measured response, and *Ŷ_i* is the predicted response (6)

MSE for the four adhesion response models and one hardness response model selected for having conforming response surfaces were computed and compared for the best fitting response model to the MRSM dataset as shown in Table 5.

Table 5 Adhesion and Hardness Response Models with Conforming Response Surfaces and their MSE Results

Adhesion	MSE	Hardness	MSE
T, R _t , T*R _t	2.3441		
T, R _t , T*R _t , T ²	2.1777	T, R _t , T*R _t , T ²	5.3806
T, R _t , T*R _t , R _t ²	1.2789		
T, R _t , T*R _t , T ² , R _t ²	0.9762		

Table 5 shows that the full adhesion model had the least MSE indicating the best fit to the MRSM dataset.

3.6 Prediction Performance Assessment

The models with conforming response surfaces were assessed for prediction performance using cross validation. Leave-one-out and leave-two-out cross validations including repeated K-Fold cross validations were used to assess prediction capability as shown in Table 6 below.

Table 6 *Results of Various Response Models' CV Computations*

CV PROCEDURE	T, R _t , T*R _t	T, R _t , T*R _t , T ²	T, R _t , T*R _t , R _t ²	T, R _t , T* R _t , T ² , R _t ²
Leave-one-out CV	4.537286 (2)	5.171649 (3)	3.864858 (1)	5.189697 (4)
Leave-Two-out CV	6.048137 (1)	8.620700 (4)	6.100692 (2)	8.213344 (4)
Repeated 5-fold CV	5.696975 (1)	6.569261 (2)	7.686296 (3)	9.255664 (4)
Repeated 6-fold CV	4.849064 (1)	5.662685 (3)	5.547741 (2)	7.243047 (4)
Sum of Positional Ranking	(5)	(12)	(8)	(16)

The rankings of each model as allocated to it due to its cross-validation value per each method of cross validation were added (the figures in brackets). The sum positional rankings selected the adhesion OLS model [T, R_t, T*R_t] as the one with the best prediction capability within the experimental space.

3.7 Optimisation

The solution methodology is illustrated in Figure 2 using Design Expert Software on the adhesion – hardness model pair [T, R_t, T*R_t] vs. [T, R_t, T*R_t, T²]. The adhesion response surface of model [T, R_t, T*R_t] was overlaid with the hardness response surface of model [T, R_t, T*R_t, T²] to give the overlay plot as shown.

The pairs of optimum cure time per rubber thickness of conveyor belt were determined using the following steps:

The pairs of optimum cure time per rubber thickness of conveyor belt were determined using the following steps:

- Generate adhesion and hardness data arrays from the response surface models with conforming response surfaces, that cover the region of interest;
- Remove all the responses that are less than customer specifications from both the adhesion and hardness arrays;
- Overlap the two trimmed arrays and clearly show the region that has both hardness and adhesion values meeting specifications; and
- Select the cure time that optimises productivity and quality for each belt rubber thickness from the final overlay array.

Since the result is not a single optimum point but a table of pairs of cure time – rubber thickness results, the above method was the simplest and most suitable for this work to the authors.

Figure 2 Illustrating the Process of Obtaining the Optimum Region using Response Surfaces

Adhesion Response Model [T, R _t , T*R _t]Array											Hardness Response Model [T, R _t , T* R _t , T ²]Array										
T	2	2	2	2	2	2	2	2	2	3	T	2	2	2	2	2	2	2	2	3	
R	1	2	3	4	5	6	7	8	9	0	R	1	2	3	4	5	6	7	8	9	0
2	8	9	9	1	1	1	1	1	1	1	2	5	5	5	5	6	6	6	6	6	6
0				0	0	0	1	1	1	2	2	7	8	9	9	0	0	0	0	0	0
1	9	9	9	1	1	1	1	1	1	1	1	1	5	5	5	5	6	6	6	6	6
9				0	0	1	1	1	1	2	2	9	7	8	9	9	0	0	1	0	0
1	9	9	1	1	1	1	1	1	1	1	1	1	5	5	5	6	6	6	6	6	6
8			0	0	1	1	1	1	2	2	2	8	8	8	9	0	0	0	1	0	0
1	9	1	1	1	1	1	1	1	1	1	1	1	5	5	5	6	6	6	6	6	6
7		0	0	0	1	1	1	1	2	2	3	7	8	9	9	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	5	5	5	6	6	6	6	6	6
6	0	0	0	1	1	1	2	2	2	2	3	6	8	9	9	0	0	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	5	5	6	6	6	6	6	6	6
5	0	0	1	1	1	2	2	2	3	3		5	8	9	0	0	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	5	5	6	6	6	6	6	6	6
4	0	1	1	1	2	2	2	3	3	3	3	4	9	9	0	0	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	5	5	6	6	6	6	6	6	6
3	1	1	1	2	2	2	3	3	3	3	3	3	9	9	0	0	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	5	6	6	6	6	6	6	6	6
2	1	1	2	2	2	3	3	3	3	3	4	2	9	0	0	1	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	5	6	6	6	6	6	6	6	6
1	1	2	2	2	3	3	3	3	4	4		1	9	0	0	1	1	1	1	0	0
1	1	1	1	1	1	1	1	1	1	1	1	1	6	6	6	6	6	6	6	6	6
0	2	2	2	3	3	3	3	4	4	4		0	0	0	0	1	1	1	1	0	0

Figure 3 Illustrating the Process of Obtaining the Optimum Region using Data Arrays

Table 7 shows the cure time against rubber thickness values extracted from the overlay array in Figure 3.

Table 7 Pair Adhesion [T, R_t, T*R_t]vs. Hardness [T, R_t, T*R_t, T²]

R (mm)	7	8	9	10	11	12	13	14	15	16	17	18	19	20
T(min.)	21	22	23	24	24	25	25	26	26	27	28	28	29	30

The same optimization process was done on the other three pairs of adhesion-hardness response models and the resulting four tables averaged into one. Table 8 below shows the averaged results.

Table 8 Average Results

R (mm)	7	8	9	10	11	12	13	14	15	16	17	18	19	20
T(min.)	21	22	23	24	24	25	25	26	26	27	27	28	29	30

Tables 7 and 8 only differ on the cure time to use for the rubber thickness of 17mm. Table 7 predicts that though the hardness will be acceptable at 61⁰Shore hardness, adhesion will be below 12N/mm. It was therefore considered safe to adopt Table 7as representative of the average results and proceed with it to validation.

3.8 Validation Run

Samples from the first seven conveyor belts vulcanised on the belting presses using the cure times in Table 7were taken and Table 9 shows the results from the validation process.

Table 9 Comparison of Predicted Results Versus he actual Measured by the Validation Process

#	R (mm)	T (min)	Ave. Adhesion (N/mm)	Ave. Hardness (⁰ Shore)
1	7	21	11.1	60
2	8	22	13.4	60
3	8	22	13.0	61
4	9	23	13.3	60
5	8	22	12.1	60
6	8	22	12.8	61
7	7	21	12.5	61

3.9 Computation of MSPE

The Table 9 was used to compute the mean squared error of prediction (MSPE) for the adhesion – hardness model pair [T, R_t, T*R_t] vs. [T, R_t, T*R_t, T²] shown in Table 10, since the dataset had not been used to fit the response models. The formula for MSPE is given below for a sample size n.

MSPE= $\frac{\sum_{i=1}^n (Y_i - Y_{Fi})^2}{n}$, where Y_i is the ith measured response, Y_{Fi} is the ith forecasted response (6)

Table 10 MSPE Values of the Adhesion – Hardness Response Model Pair [T, R_t, T*R_t]vs. [T, R_t, T*R_t, T²]

Adhesion		Hardness	
	MSPE		MSPE
T, R _t , T*R _t	0.7086	T, R _t , T*R _t , T ²	0.57143

3.10 Comparison with Stephen's Rule

This part was focused on validating MRSM as an alternative method to Stephens' rule of thumb. This is important as a single minute saved per press can mean an hour of vulcanization time saved for a standard 300m long conveyor belt. Computational analysis showed that MRSM results get more efficient than Stephen's rule of thumb with increasing rubber thickness. This agrees with theory since Stephen's rule of thumb assumes a simple straight-line relationship between cure time and rubber thickness whilst the rheotrace gives a different picture. On the quality side, MRSM considers both requirements of adhesion of constituent components and cover hardness whilst Stephen's rule only considers hardness as it is designed to estimate single compound variation of cure time with product thickness.

4. Discussion

4.1 Use of Response Surface Conformity to Avoid Model Selection Criteria Uncertainty

Response surface analysis has always been an important step in multiresponse surface methodology, though relegated to secondary status to classical model selection by practitioners. Practice has been that best response models were first selected using model selection criteria based on fitness to the MRSM dataset instead of prediction capability before response surface analysis was done as the initial part of the optimisation stage. Selection of best models using classical model selection criteria assumed that fitness to MRSM dataset signified response surface conformity, which is wrong. Response surface conformity can only be ascertained by response surface analysis in the presence of prior knowledge of the expected behaviour of the 'true' response surface. When modelling of small sample size datasets, response surface uncertainty cannot be ignored, and should be considered critical to the credibility of results. The use of response surface conformity to avoid the problem of classical model selection criteria disagreement was successful. Though response surface analysis successfully reduced the hardness candidate response models from thirty-one to one, it could only reduce the adhesion response models to four. The four adhesion response models with conforming response surfaces were each optimised with the one hardness model with a conforming response model to produce four sets of results which were averaged and used to run the production process.

4.2 Effectiveness of Employed Strategies to Manage Small Sample Size Problems

4.2.1 Avoidance of best model selection with classical model selection criteria

Avoiding the use of classical model selection criteria successfully evaded the related problems of small sample size selection criteria inefficiency and uncertainty. Averaging the four pairs of results ensured that selection of a single best model using selection criteria was successfully avoided.

4.2.2 Use of Multiple Cross Validations

As Table 6 shows, even different cross validations do not necessarily agree. Use of multiple cross validations and then summing rankings is meant to add rigour to the

response model prediction assessment. From Tables 5 and 6, it comes out clearly that the best fitting model is not necessarily the best prediction model. However, the two uncertainties are happening within the context of conforming response surfaces and justify the non-selection of a best model and therefore the option to average results.

4.2.3 Modelling Credibility

Small sample size modelling credibility can only be solved by adding rigour to the problem solution methodology. The use of response surface conformity to select candidate models ensured avoidance of classical model selection criteria uncertainty over the best response model and the problem of small sample criteria bias. The use of averaged results from four different sets of test results added rigour to the problem solution methodology.

4.3 Effect of Mismatched Centres

The positioning of the desired region within the experimental space is as shown in APPENDIX C. The diagram shows two polygons, the outer (blue polygon) being of the 2-factor CCD experimental design and the inner one (orange polygon) representing the process region of interest. Of note is the fact that the desired region fell within the region of experimental design though the centres of the two polygons did not coincide. However, the mismatch in centres did not seem to have any effect on the results. As long as the response models had conforming response surfaces in the region of interest, the results were expected to be credible. Even the extreme point ($T=30\text{min}$, $R_t=7.2\text{mm}$) did not seem to have any weird adhesion and hardness results. Insistence on response surface conformity assisted in ensuring that the prediction accuracy of response models remained reasonably acceptable within the whole experimental region.

5. Managerial Implications

5.1 Usability of MRSM and Results

The rubber thickness - cure time results of Table 7, can be used to obtain the cure time of any belt thickness of the same cover and skim compounds for vulcanization under the same temperature and pressure. The fact that working results were obtained from this study implies that MRSM is quite usable at the shop floor for efficiently solving problems of two independent variables or less without any complicated machinery but basic conveyor belt laboratory equipment. MRSM also gives more efficient cure times than Stephen's rule of thumb which is good for shop floor productivity and product quality. MRSM, unlike Stephen's rule, considers the satisfaction of both adhesion and cover hardness requirements of customers.

5.2 Future Experiments

If the technical specifications of the cover or skim compound change, either independently or simultaneously, the multi-response surface experiment has to be re-run using the generic model as given by equation (3).

$$\text{Adhesion/Hardness} = \text{function of (cure time, total rubber thickness)} + \text{error term} \quad (3)$$

5.3 Continued Testing (Continuous Improvement)

For a balanced, reliable and more accurate assessment of prediction capability of response models, MSPE computations will have to be repeated in the future as more data is accumulated from running the actual production process which is obviously different from the laboratory process. This can be done as part of process continuous improvement.

6. Future Research

6.1 Application of MA in MRSM to Improve Prediction Capability

The application of model averaging to MRSM will be an interesting research direction especially with the fact that response surface analysis does not necessarily result in best response model. The averaging of models for better prediction accuracy need to be compared with the simple averaging of results.

6.2 Combining Specification Change with Cure Time Experiments for Efficiency

The experimental work reported above was done after that of determining the right specifications of the rubber compounds. There is need to come up with a more efficient way that combines the mixture experiments of optimising the compound specifications and the rubber thickness – cure time experiments for optimising process conditions.

7. Conclusion

MRSM is quite usable at the shop floor for efficient and effective quality and productivity improvements. However, rigour is required to ensure credibility of results because MRSM datasets are normally small sample size in nature. The conformity of response surfaces can be used, where experience or knowledge or previous process data is available, in place of classical model selection criteria to select candidate models for optimisation. This is limited, however, to two input variable response processes because of the ease of developing two-dimensional response data arrays and three-dimensional response surfaces.

8. Appendices

Appendix A

Shows the general rheotrace for rubber compounds. A rheotrace shows how rubber vulcanizes with time under a given temperature by plotting the torque resistance of rubber as vulcanisation proceeds.

Appendix B

Showing the contextual framework of MRSM as revealed in literature.

Appendix C

Shows the relative placing of the process region of interest within the experimental region. The blue polygon defines the 2-factor CCD design experimental space, whilst the red polygon defines the process region of interest.

Supplementary Materials are available on request by emailing the corresponding author.

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