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Optimization of Process Parameters for Green Composites in Abrasive Water Jet Machining Process Using Neuro-Regression Analysis

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Abstract
This study aims to develop a design procedure for optimizing the abrasive water jet machining (AWJM) process in green composites. Multiple non-linear neuro-regression analysis has been performed methodically to overcome insufficient approaches to modeling-design-optimizing green composites in AWJM. First, the model generation process is carried out according to three criteria: linearity, order, and functions used in the model. Next, $R^2_{training}$, $R^2_{testing}$, and $R^2_{validation}$ values have been checked for the validity of the models. Then, the machining parameters have been optimized by applying a numerical non-linear global optimization algorithm, Simulated Annealing. Pressure within the pumping system (PwPS), stand-off distance (SoD), and nozzle speed (NS) are design variables; surface roughness (Ra) and process time (PT) are objective functions of introduced mathematical optimization problems. The numerical result shows that the optimum process parameters obtained are PwPS (150 MPa), SoD (3.5 mm), and NS (125 mm/min). This novel optimization approach is also feasible for another modeling design optimization problem. The proposed design can be used as a systematic framework for parameter optimization in environmentally conscious manufacturing processes.
Keywords: Abrasive water jet machining; green composite; neuro-regression; optimization.

1. Introduction

Polymer-based composites have been widely used in manufacturing industries for several years. However, the rising concerns towards the ecological issues and the need for more flexible materials led to the usage of polymer-based composites filled with natural organic fillers. Therefore, this type of material is often referred to as green composites (GC) or natural filler reinforcement composites (NFRC). These natural fillers are usually drawn from natural plant, animal, and renewable sources and have exceptional merits over the synthetic fillers/fibers such as low cost, renewable in nature, less abrasive, easy to be destroyed, lower specific weight, environment friendly, and also non-toxicity.

The past literature reveals the application of various forms of natural fillers such as flax, cellulose, cotton, sisal, kenaf, curaua, jute, banana, roselle, pineapple, bamboo, rice, and wood as reinforcing agents in order to improve the mechanical properties and obtain the properties needed in actual applications [1].

Peng P. and She D. study bamboo, a material, and various a compilation have been made about its potential and applications in the fields. In its internal structure, the hemicellulose structure was examined, and physical and thermal analysis by purification was made. The film layer is produced from pure hemicellulose [2].

In the research of Oksman and Selin [3], it is shown that the elastic modulus of wood fibers is approximately 40 times higher than that of polyethylene, and the strength is about 20 times higher. Nevertheless, many works devoted the mechanical behavior and machinability of the natural fiber-reinforced polymer composites none of the studies were found in the literature on machining behavior of the wood dust-based polymer composite.

Getu and Sahu [4] manufactured the composites which are undergone for testing of bending rigidity, shear, and absorbency. The tests conducted on the green composites developed reveal that they are suitable for usage fit for all users' fields. Furthermore, bagasse, banana, and sisal fibers have excellent tensile strength, allowing them to be used without finishing. Finally, it is concluded that it significantly reduces production and processing costs while also preserving the environment because the user and the environment will not be harmed during the manufacturing, processing, or disposal of this composite.

Sorgun [5] manufactured the composites with polypropylene matrix using two different particles (100 μm below, 100-200 μm) obtained by grinding sandalwood. With the addition of 5% SA into PP, the tensile strength of PP increased by 10.2%. However, it was observed that the tensile strength decreased when the amount of SA added into the PP was increased. The highest value for the modulus of elasticity was determined in PP composite reinforced with less than 100-micron SA particles. 20% SA reinforced PP elasticity module increased 29.1% compared to PP elasticity module. When SA is added to PP, a decrease in the bending strength of PP has been determined in general, especially 100 μm above PP. The opposite was seen in the bending modulus. Increasing the amount of SA increased the PP bending modulus [5].

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Similarly, Gökdemir [6] manufactured the composites with polypropylene matrix using two different particles (100 μm below, 100-200 μm) obtained by sugar beet pulp. It was observed that the tensile strength decreased when the amount of SP added into the PP was increased. In addition, it was observed that when the SP amount was increased, the modulus of elasticity increased. Thus, in general, as the amount of SP increased, bending strength decreased [6].

Raju et al. investigate the feasibility of using groundnut shell particles in the manufacture of composite panels. Groundnut shell particles were used to make composites with loadings of 20 percent, 30 percent, 40 percent, 50 percent, and 60 percent (by weight). The results showed that the panels might be made with up to 30% peanut husk without impairing their usage. Furthermore, because of its mild mechanical qualities, low moisture content, and low water absorption, groundnut shell particles can be used to substitute for wood in fabricating particle boards in the indoor environment [7].

AWJM is one of the most widely used non-conventional machining processes. This process is a very effective method for precision machining hard and brittle materials, and it is a non-contact, less inertia, and faster machining process. This offers various advantages such as reduced waste materials, less heat-affected zone, higher flexibility, versatility, and minimal force during machining [1]. However, the performance characteristic of this process is directly or indirectly influenced by the process parameters, which directly affects the efficiency of the manufacturing process. Thus, optimization of process parameters is a vital task to achieve green AWJM.

On the other hand, several researchers have profited from various optimization approaches for the AWJM process during the machining of different materials, such as the Taguchi method on machining of SKD61 mold steel [8], transformation-induced plasticity (TRIP) sheet steels, glass sheets, and glass/epoxy composite artificial neural network (ANN) model on machining of AA 7075 aluminum alloy [9]; ANN-genetic algorithm (GA) on machining of 6063-T6 aluminum alloy[10]; artificial neural network (ANN)-simulated annealing (SA) and SA-GA on machining of AA 7075 aluminum alloy [11, 12]; neuro-fuzzy approach on machining of 6063-T6 aluminum alloy[13]; analysis of variance (ANOVA) and Derringer-Suich multi-criteria decision modeling approach on machining of AISI 4340 and aluminum 2219 [14]; Taguchi-fuzzy decision method on machining of coal [15]; RSM with sequential approximation optimization (SAO) method on machining of alumina ceramic [16]; neural network (NN) model on machining of titanium [17]. However, none of the literature researchers have worked on optimizing process parameters for green AWJM on machining of WDFRP composites [1].

This study aims to introduce a design procedure for optimizing the abrasive waterjet machining (AWJM) process in green composites. First, multiple non-linear neuro-regression analysis was methodically performed to overcome the inadequate approaches to numerical part. The values of $R^2_{tranining}$, $R^2_{testing}$, and $R^2_{validation}$ were checked for the validity of the models. Then, processing parameters are optimized by applying numerical non-linear global optimization algorithm, Simulated Annealing. Pressure within the pumping system (PwPS), stand-off distance (SoD), and nozzle speed (NS) are design variables; surface roughness (Ra) and processing time (PT) are objective functions of the introduced mathematical optimization problems. In order to perform this procedure, we used the experimental data in the study [1], which has been investigated before in the literature on this subject.

2. Methodology

2.1. Modelling

At the commencing of the current research, to reap the most efficient values for operational parameters, the modeling system has been implemented to receive the most potent mathematical model. In this way, a combination of artificial neural networks and regression analysis is used. In this approach, all data is divided into three sets comprising 80%, 15%, and 5% of the given data. The data's first, second, and third portions are used for training, testing, and validation, respectively. The training process aims to minimize the error between the experimental and predicted values by modifying the regression models and their coefficients given in Table 1. After the training part, the checking out procedure was once used to eliminate the uncertainties generated via the regression items. The feasibility of suitable models similar to R^2 values is then checked by testing out if the models' severe elements are within the targeted interval of each running parameter. Next, the model analyses are made to appreciate main explanations such as model linearity, model order, and functions, affecting each the ability of prediction and the model's feasibility. After analyses are finished, a modified non-linear model is determined to use for primary regression analyses of output parameters. These modified items are shown in Table 2.

Table 1. *Multiple Regression Model Types Including Linear, Second and Third Order; Exponential, Trigonometric, Logarithmic and Polynomial.*

Model Name	Nomenclature	Formula
Multiple Linear	L	F = $a_0 + a_1x1 + a_2x2 + a_3x3$
Second Order Multiple Nonlinear	SONL	F = $a_0 + a_1x1 + a_2x2 + a_3x3 + a_4x1^2 + a_5x2^2 + a_6x3^2 + a_7x1x2 + a_8x1x3 + a_9x2x3$
Third Order Multiple Nonlinear	TONL	F = $a_0 + a_1x1 + a_2x2 + a_3x3 + a_4x1^2 + a_5x2^2 + a_6x3^2 + a_7x1x2 + a_8x1x3 + a_9x2x3 + a_{10}x1^3 + a_{11}x2^3 + a_{13}x3^3 + a_{14}x1^2x2 + a_{12}x1^2x3 + a_{13}x2^2x1 + a_{14}x2^2x3 + a_{15}x3^2x1 + a_{16}x3^2x2 + a_{17}x1x2x3$
Second Order Multiple Nonlinear Logarithm	SOMNL	F = $a_0 + a_1Logx1 + a_2Logx2 + a_3Logx3 + a_4Logx1^2 + a_5Logx2^2 + a_6Logx3^2 + a_7Logx1x2 + a_8Logx1x3 + a_9Logx2x3$
Third Order Multiple Nonlinear Logarithm	TOMNL	F = $a_0 + a_1Logx1 + a_2Logx2 + a_3Logx3 + a_4Logx1^2 + a_5Logx2^2 + a_6Logx3^2 + a_7Logx1x2 + a_8Logx1x3 + a_9Logx2x3 + a_{10}Logx1^3 + a_{11}Logx2^3 + a_{13}Logx3^3 + a_{14}Logx1^2x2 + a_{12}Logx1^2x3 + a_{13}Logx2^2x1 + a_{14}Logx2^2x3 + a_{15}Logx3^2x1 + a_{16}Logx3^2x2 + a_{17}Logx1x2x3$
Second Order Multiple Nonlinear Trigonometric	SOMNT	F = $a_0 + a_1Sinx1 + a_2Sinx2 + a_3Sinx3 + a_4Sinx1^2 + a_5Sinx2^2 + a_6Sinx3^2 + a_7Sinx1x2 + a_8Sinx1x3 + a_9Sinx2x3$
Third Order Multiple Nonlinear Trigonometric	TOMNT	F = $a_0 + a_1Sinx1 + a_2Sinx2 + a_3Sinx3 + a_4Sinx1^2 + a_5Sinx2^2 + a_6Sinx3^2 + a_7Sinx1x2 + a_8Sinx1x3 + a_9Sinx2x3 + a_{10}Sinx1^3 + a_{11}Sinx2^3 + a_{13}Sinx3^3 + a_{14}Sinx1^2x2 + a_{12}Sinx1^2x3 + a_{13}Sinx2^2x1 + a_{14}Sinx2^2x3 + a_{15}Sinx3^2x1 + a_{16}Sinx3^2x2 + a_{17}Sinx1x2x3$
Second Order Multiple Nonlinear Exponential	SOMNE	F = $a_0 + a_1e^{x1} + a_2e^{x2} + a_3e^{x3} + a_4e^{x1^2} + a_5e^{x2^2} + a_6e^{x3^2} + a_7e^{x1x2} + a_8e^{x3x2} + a_9e^{x1x3}$
Third Order Multiple Nonlinear Exponential	TOMNE	F = $a_0 + a_1e^{x1} + a_2e^{x2} + a_3e^{x3} + a_4e^{x1^2} + a_5e^{x2^2} + a_6e^{x3^2} + a_7e^{x1x2} + a_8e^{x3x2} + a_9e^{x1x3} + a_{10}e^{x2^3} + a_{11}e^{x1^3} + a_{12}e^{x3^3} + a_{13}e^{x2^2x1} + a_{14}e^{x2^2x3} + a_{15}e^{x1^2x2} + a_{16}e^{x1^2x3} + a_{17}e^{x3^2x1} + a_{18}e^{x3^2x2}$

2.2. Optimization

Optimization is the process of obtaining the most appropriate solution by providing certain constraints in line with the given purpose or objectives. To express it mathematically; Optimization can be briefly defined as minimizing or maximizing a function. Also, optimization can maximize productivity, strength, reliability, longevity, efficiency, and utilization. The techniques used in an optimization problem can be categorized into traditional and non-traditional. The traditional method starts with the initial solution and with each successive iteration converges to the optimal solution. This convergence depends on the selection of initial approximation. These methods are not suited for discontinuous objective function. So, the need for a non-traditional method was felt [18-20]. The most widely used non-traditional optimization methods are genetic algorithms, simulated annealing, and particle swarm. The reliability of the outcomes taken from a non-traditional (stochastic) optimization evaluation can also be improved via utilizing a couple of methods. The most difficult mathematical optimization problems have the following issues:

- Multiple non-linear objective functions,
- Objective functions having many local extremum points,
- Mixed-integer (discrete)-continuous nature of the design variables, and
- Non-linear constraints [18].

In this paper, the optimization scenarios mentioned include the challenges given in the first three items.

2.2.1 Problem Definition

By using the above-described methods, the optimal analysis of process parameters of green composite in AWJM was organized as follows;

- The data shown in Table 3 are from the reference study [1]. They have modeled the processing time and surface roughness input parameters with Response Surface Method.
- Three base functional structures were proposed for modeling, and the boundedness of the functions was evaluated for appropriateness in terms of $R^2_{training}$, $R^2_{testing}$, and $R^2_{validation}$ values.
- A new updated non-linear model is generated for each of the output parameters from the result of the base models, and then, these modified models are also tested in terms of R^2 values.
- Two different optimization scenarios were introduced using the appropriate models, which were solved by a direct search method.

2.2.2 Optimization Scenarios

Scenario (a) In this optimization problem, all the design variables are assumed to be real numbers for all the objective functions, and the search space is continuous. For this case, the constraints are 150 < PwPS < 300, 1.5 < SoD < 3.5, 125 < NS < 225. The main goal is to get optimum values for objective functions. Mathematically, limits of the objective function can also be obtained by this approach.

Scenario (b) Based on only the prescribed experimental setup, more specific optimization problem can also be defined as involving (i) optimization of objective functions, (ii) all the design variables are assumed to be real numbers, and (iii) the constraints are PwPS ∈ {150, 225, 300}; SoD ∈ {1.5, 2.5, 3.5}; NS ∈ {125, 175, 225}.

Table 2. *Model Formula for Output.*

Output Name	Modified Model Formula	Model
Ra	F = $a_0 + a_1 Logx1 + a_2 Logx2 + a_3 Logx3 + a_4 Logx1^2 + a_5 Logx2^2 + a_6 Logx3^2 + a_7 Logx1x2 + a_8 Logx1x3 + a_9 Logx2x3$	-1.094721042052923 $+ 0.048718366176467354\text{Log}[x1]$ $+ 0.024359183088233656\text{Log}[x1^2]$ $- 0.047892896045495015\text{Log}[x2]$ $+ 0.03550664102887537\text{Log}[x1x2]$ $- 0.023946448022747608\text{Log}[x2^2]$ $+ 0.030129863589708566\text{Log}[x3]$ $+ 0.019986916583215445\text{Log}[x1x3]$ $+ 0.021228411293550627\text{Log}[x2x3]$ $+ 0.015064931794854283\text{Log}[x3^2]$
PT	F = $a_0 + a_1 Logx1 + a_2 Logx2 + a_3 Logx3 + a_4 Logx1^2 + a_5 Logx2^2 + a_6 Logx3^2 + a_7 Logx1x2 + a_8 Logx1x3 + a_9 Logx2x3$	-1.9849045387424702 $- 0.01071578210330012\text{Log}[x1]$ $- 0.005357891051649882\text{Log}[x1^2]$ $- 0.12693642357351628\text{Log}[x2]$ $- 0.010586200398944654\text{Log}[x1x2]$ $- 0.06346821178675836\text{Log}[x2^2]$ $+ 0.15758114439411514\text{Log}[x3]$ $+ 0.03462614296942368\text{Log}[x1x3]$ $+ 0.11375733676330331\text{Log}[x2x3]$ $+ 0.07879057219705755\text{Log}[x3^2]$

Table 3. *Experimental Data [1].*

Exp. No	Inputs			Outputs	
	PwPS (MPa)	SoD (mm)	NS (mm/min)	Ra	PT
1	300	1.5	175	0.2761	0.4012
2	150	2.5	225	0.1980	0.4125
3	300	2.5	125	0.2570	0.1058
4	150	3.5	175	0.1290	0.1853
5	300	2.5	225	0.2981	0.4663
6	150	1.5	175	0.1889	0.3250
7	225	2.5	175	0.1957	0.2568
8	225	3.5	225	0.2456	0.3425
9	225	2.5	175	0.2214	0.3805
10	225	1.5	125	0.1953	0.1569
11	150	2.5	125	0.1190	0.1137
12	225	1.5	225	0.2640	0.4472
13	300	3.5	175	0.2583	0.1665
14	225	2.5	175	0.2012	0.2912
15	225	3.5	125	0.1630	0.1026

3. Results

3.1 Determination of main effects on surface roughness (Ra)

In this section, the effect of machining parameters on Ra has been determined using the *NonlinearModelFit* solver of Wolfram Mathematica for the experimental Ra. It has been observed from Table 3 that the variables PwPS (x1) and NS (x3) have positive effects and SoD (x2) harms the Ra. The process variables PwPS and NS are the most influencing parameters and can predict the Ra within the control limits. The value of R^2 is calculated to be 0,996642 for Ra (See Table 4). Higher the R^2 coefficient gives a satisfactory model to the experimental data. Finally, the adequacy and fitness of the model are calculated by adjusted R^2 values. The high value of adjusted R^2 (0,996642) for Ra indicates that the number of experimental data used to develop the model is compatible with the relevant model. It is seen that the surface roughness is mainly affected by PwPS and NS. Surface roughness is increased significantly from 0.125728 to 0.285823 µm as PwPS is increased by 150 to 300 MPa. As for NS, a slight increment of surface roughness occurred when NS is increased from 125 to 225 mm/min with 0.125728 to 0.26733 µm.

Meanwhile, surface roughness is observed to decrease as SoD increased from 1.5 to 3.5 mm. Since PwPS and NS showed higher percentage contribution than other factors (SoD), they can be considered the most significant to the surface roughness. Therefore, the calculations are performed by increasing the PwPS and NS from 150 to 300 MPa and simultaneously by decreasing SoD from 3.5 to 1.5 mm. Finally, the optimal surface roughness is obtained when machining parameters set at PwPS, SoD, and NS are 300 MPa, 1.5 mm, and 225 mm/min, respectively (See Table 5).

3.2 Determination of main effects on process time (PT)

In this section, the effect of machining parameters on PT has been determined similar to that of Ra. It has been observed from Table 3 that the variables NS (x3) have a positive effect, SoD (x2) and PwPS (x1) harm the PT. The process variables NS are the most influencing parameters and can be used to predict the PT within the control limits. The R^2 is 0.979413 for PT. It has been examined from the Table 3 that the process time is mainly affected by NS. The processing time is increased significantly from 0.0785736 to 0.478729 s as NS was increased by 125 to 225 mm/min.

Meanwhile, the processing time is observed to decrease as SoD increased from 1.5 to 3.5 mm. Since NS shows a higher percentage contribution than the other factors (SoD), they can be considered most significant to the processing time. Therefore, the alternative calculations are also performed by increasing the NS from 125 to 225 mm/min and simultaneously decreasing SoD from 3.5 to 1.5 mm. Finally, the optimal process time is obtained when machining parameters are set at SoD of 1.5 mm and NS of 225 mm/min.

Table 4. *The candidate model results and their R^2 values.*

Minimum Value of PT	Model	$R^2_{training}$	$R^2_{testing}$	$R^2_{validation}$
0.0775151	TOMNL	0.995707	0.519515	-0.161361
0.815783	SONL	0.995707	-0.285542	-3.06543
0.027278	TONL	0.995707	0.0795861	-2.11266
-0.509278	SOMNT	0.995707	-0.462265	0.45073
-0.701173	TOMNT	0.995707	-1.07981	-8.572680
-0.369327	TOMNT	0.995707	-0.0326963	-2.12837
-7.08517	SOMNT	0.995707	0.619977	-6.36817
-0.104237	TOMNE	0.960279	-2.02549×10^{6}	-2.36169
-1.02783368×10^{11}	SOMNE	0.960279	-2.82425×10^{6}	0.435343
0.0300375	M1	0.987399	0.653279	0.974805
-0.147157	M2	0.995707	0.862176	-2.47803
0.0696715	M3	0.987399	0.653279	0.974805
-0.017173	M4	0.995707	0.034263	-1.32716
-0.0595981	M5	0.987399	-1.21209	-6.18308

Table 5. *Results of the optimization problems for the selected models.*

Response Parameters	Goal	Optimum			Target	Model
		PwPS	SoD	NS		
Ra	Minimum	150	3.5	125	0.119	0.112589
PT	Minimum	150	3.5	125	0.1026	0.077516

4. Conclusions

This work proposed a design optimization based on non-linear multiple neuro regression analysis for machining of a biocomposite in AWJM processes. Thus, a novel approach based on a modeling-design-optimization process to design an optimum surface roughness and process time has been introduced. The purpose of the research study is to reveal the regression model investigated as the best model to predict the experimental results of Ra, PT on input parameters and then optimize inputs. A direct search technique, Simulated Annealing, is used including stochastic approaches, during the optimization process. The numerical results that optimum cutting parameters obtained are 150 MPa, 3.5 mm, and 125 mm/min for PwPS, SoD, and NS, respectively. The results also indicate that the parameters PwPS and NS are the most significant factors for Ra, while only parameter NS for PT. Therefore, it is concluded that the developed mathematical model is significant and adequate for process parameter selection and prediction of AWJM output parameters on the machining of green composites. Thus, this approach can be used as a systematic framework model for predicting response parameters in green manufacturing applications and helps in selecting optimal machining parameters in practical work for green manufacturing industries.

Declaration of Interest

The authors declare that there is no conflict of interest.

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APPENDIX

Model Name	Model
TOMNL	$-2.806528296855611 + 0.24576645769296207\mathrm{Log}[x1] + 0.04895764577773693\mathrm{Log}[x1]^2$ $- 0.015108744635239061\mathrm{Log}[x1]^3 - 2.3375909888328423\mathrm{Log}[x2]$ $+ 0.37156869342381355\mathrm{Log}[x1]\mathrm{Log}[x2]$ $- 0.007974927955401436\mathrm{Log}[x1]^2\mathrm{Log}[x2] + 0.7544078020289587\mathrm{Log}[x2]^2$ $- 0.7427468406531201\mathrm{Log}[x1]\mathrm{Log}[x2]^2 + 3.7945776182670783\mathrm{Log}[x2]^3$ $+ 0.06454365663401485\mathrm{Log}[x3] + 0.07552076059510957\mathrm{Log}[x1]\mathrm{Log}[x3]$ $+ 0.00015695539522465223\mathrm{Log}[x1]^2\mathrm{Log}[x3]$ $+ 0.2976846759003845\mathrm{Log}[x2]\mathrm{Log}[x3]$ $+ 0.1123559335083702\mathrm{Log}[x1]\mathrm{Log}[x2]\mathrm{Log}[x3]$ $- 1.2931833357284106\mathrm{Log}[x2]^2\mathrm{Log}[x3] + 0.022028436007974182\mathrm{Log}[x3]^2$ $+ 0.0005379959833349629\mathrm{Log}[x1]\mathrm{Log}[x3]^2$ $+ 0.13856252558673193\mathrm{Log}[x2]\mathrm{Log}[x3]^2 - 0.015170136062410909\mathrm{Log}[x3]^3$
SONL	$-0.8877456875662202 + 0.008241494259063021x1 - 0.000011435172427547529x1^2$ $- 0.28367413885945597x2 - 0.0009099999999999931x1x2$ $+ 0.04247284490495425x2^2 + 0.006194517222810836x3$ $- 0.0000069866666666666543x1x3 + 0.001296913796198187x2x3$ $- 0.000015430862038018096x3^2$
TONL	$-0.26427947911334526 + 0.001670198115672160 8x1 + 0.0000049000432190063 8x1^2$ $- 1.436362198383393 \times 10^{-8}x1^3 - 0.1457247612928245x2$ $+ 0.00021909952693669683x1x2 - 0.0000018898068249534 62x1^2x2$ $- 0.021970532359016786x2^2 - 0.000025565211545939657x1x2^2$ $+ 0.008686457799320446x2^3 + 0.0016337594337852773x3$ $+ 0.0000080226244562416 09x1x3 - 9.224429991622914 \times 10^{-9}x1^2x3$ $+ 0.0003024891345997836x2x3 - 8.157681575534157 \times 10^{-8}x1x2x3$ $- 0.000039369838958494 37x2^2x3 + 0.0000070978043700599 59x3^2$ $- 2.470454083985247 \times 10^{-8}x1x3^2 + 0.0000031074693353768 99x2x3^2$ $- 4.267499092338159 \times 10^{-8}x3^3$
SOMNT	$0.3464813339886176 + 0.3831843213555272\mathrm{Cos}[x1] - 0.6100846360385241\mathrm{Cos}[x1]^2$ $- 0.49513849393352827\mathrm{Cos}[x2] - 0.15714002906460747\mathrm{Cos}[x1]\mathrm{Cos}[x2]$ $- 0.3962049453066922\mathrm{Cos}[x2]^2 + 0.38278250379852247\mathrm{Cos}[x3]$ $- 0.10791087170147802\mathrm{Cos}[x1]\mathrm{Cos}[x3] + 0.6377570713976038\mathrm{Cos}[x2]\mathrm{Cos}[x3]$ $- 0.4390785559194609\mathrm{Cos}[x3]^2$
TOMNT	$0.1686792618833355 + 0.26568673069337423\mathrm{Cos}[x1] + 0.24262614319066322\mathrm{Cos}[x1]^2$ $- 0.08130731078829158\mathrm{Cos}[x1^3] - 0.02442678715695238\mathrm{Cos}[x2]$ $- 0.34383374206498113\mathrm{Cos}[x1]\mathrm{Cos}[x2] + 0.08780713412470981\mathrm{Cos}[x2]^2$ $+ 0.06281327558625166\mathrm{Cos}[x1^2x2] - 0.06868399476131787\mathrm{Cos}[x1x2^2]$ $- 0.030587651869661527\mathrm{Cos}[x2^3] - 0.01637814399953465 8\mathrm{Cos}[x3]$ $- 0.14736509640310413\mathrm{Cos}[x1]\mathrm{Cos}[x3] + 0.1619725525663956\mathrm{Cos}[x2]\mathrm{Cos}[x3]$ $- 0.30212965117886503\mathrm{Cos}[x3]^2 + 0.039158811483846\mathrm{Cos}[x1^2x3]$ $+ 0.02613820585098387\mathrm{Cos}[x1x2x3] - 0.1347167581855755\mathrm{Cos}[x2^2x3]$ $+ 0.02164619613189358\mathrm{Cos}[x1x3^2] - 0.04538789588955367\mathrm{Cos}[x2x3^2]$ $+ 0.10386828830712264\mathrm{Cos}[x3^3]$
TOMNT	$0.010956406333690832 - 0.012880869509242655\mathrm{Sin}[x1] + 0.014056843488704831\mathrm{Sin}[x1]^2$ $+ 0.04217709102028845\mathrm{Sin}[x1^3] + 0.014644987047005769\mathrm{Sin}[x2]$ $- 0.021633011430284007\mathrm{Sin}[x1]\mathrm{Sin}[x2] + 0.01039746477383733\mathrm{Sin}[x2]^2$ $+ 0.003971444244157852\mathrm{Sin}[x1^2x2] + 0.008361173625667672\mathrm{Sin}[x1x2^2]$ $+ 0.01214925494581947\mathrm{Sin}[x2^3] - 0.03934453616300522\mathrm{Sin}[x3]$ $+ 0.044824142835632026\mathrm{Sin}[x1]\mathrm{Sin}[x3] - 0.03896417187256429\mathrm{Sin}[x2]\mathrm{Sin}[x3]$ $+ 0.07476462148286063\mathrm{Sin}[x3]^2 + 0.00881518563270643\mathrm{Sin}[x1^2x3]$ $- 0.0017988745823680223\mathrm{Sin}[x1x2x3] - 0.044227527857748326\mathrm{Sin}[x2^2x3]$ $+ 0.03145113293156068\mathrm{Sin}[x1x3^2] + 0.09168632058997019\mathrm{Sin}[x2x3^2]$ $+ 0.18111218870491896\mathrm{Sin}[x3^3]$
SOMNT	$-1.506481581746801 + 0.6633113978936133\mathrm{Sin}[x1] + 0.1985238688002158\mathrm{Sin}[x1]^2$ $- 1.2260355188064873\mathrm{Sin}[x2] - 0.942131397477979\mathrm{Sin}[x1]\mathrm{Sin}[x2]$ $+ 0.0012381323094438814\mathrm{Sin}[x2]^2 - 5.608721192285001\mathrm{Sin}[x3]$ $- 0.4360987320614480 6\mathrm{Sin}[x1]\mathrm{Sin}[x3] - 0.5709493827365565\mathrm{Sin}[x2]\mathrm{Sin}[x3]$ $- 3.031580877733221\mathrm{Sin}[x3]^2$

TOMNE	$0.3584661145336239 - 2.12909008899949 \times 10^{-132}e^{x1} - 1.096098206972239 \times 10^{-262}e^{2x1} - 5.642933032919888 \times 10^{-393}e^{3x1} - 0.007060458558848227e^{x2} - 0.00010183898445452515e^{2x2} + 0.000002467931386099823e^{3x2} - 6.929418861601583 \times 10^{-134}e^{x1+x2} - 3.567403572448321 \times 10^{-264}e^{2x1+x2} + 2.993669089540962 \times 10^{-136}e^{x1+2x2} + 4.609101620564808 \times 10^{-100}e^{x3} + 8.858452386953752 \times 10^{-198}e^{2x3} + 1.702548243714151 \times 10^{-295}e^{3x3} + 5.208436540978609 \times 10^{-208}e^{x1+x3} + 2.681407415863556 \times 10^{-338}e^{2x1+x3} + 4.300154303735925 \times 10^{-101}e^{x2+x3} + 1.048472099495983 \times 10^{-209}e^{x1+x2+x3} + 3.139294829186729 \times 10^{-102}e^{2x2+x3} + 1.911200782591157 \times 10^{-295}e^{x1+2x3} + 8.26467179335718 \times 10^{-199}e^{x2+2x3}$
SOMNE	$0.3629282391556579 - 3.880889743896887 \times 10^{-132}e^{x1} - 1.997959744268643 \times 10^{-262}e^{2x1} - 0.008557111121914379e^{x2} + 0.00002101373912522714e^{2x2} - 2.211475417414493 \times 10^{-134}e^{x1+x2} + 1.014919706310555 \times 10^{-99}e^{x3} + 1.95062262346722 \times 10^{-197}e^{2x3} + 1.17422615249896 \times 10^{-207}e^{x1+x3} + 7.112959103485582 \times 10^{-101}e^{x2+x3}$
M1	$-6.884621908691676 - 0.003310160990502853x1 - 0.1795128398745423x2 - 0.0028865522932737583x3 + 0.1549702875629974\mathrm{Log}[x1^2] + 0.2261277483530626\mathrm{Log}[x1x2] - 0.14643670101558337\mathrm{Log}[x2^2] + 0.18411179012802942\mathrm{Log}[x1x3] + 0.31260647329654834\mathrm{Log}[x2x3] + 0.21568130611522568\mathrm{Log}[x3^2]$
M2	$-0.977969004641075 + 0.0027621273809966 8x1 + 0.2240464206199017x2 - 0.0035032237523387314x3 - 0.10258271436507711\mathrm{Cos}[x1x2] + 0.013490427465798985\mathrm{Cos}[x1x3] - 0.14848120780365992\mathrm{Cos}[x2x3] - 0.3146631799697366\mathrm{Log}[x1^2] - 0.4152539728710519\mathrm{Log}[x2^2] + 0.4563601853244841\mathrm{Log}[x3^2]$
M3	$-0.0015204361198190176 + 0.000003025337164551866x1 - 0.0961700305498646x2 + 0.0025749505639698547x3 - 0.054828121539106836\mathrm{Cos}[x1^2] + 0.025372061348625713\mathrm{Cos}[x2^2] + 0.07980279973963535\mathrm{Cos}[x3^2] - 0.005330598161851888\mathrm{Log}[x1x2] + 0.004122547995664559\mathrm{Log}[x1x3] + 0.007196294643862707\mathrm{Log}[x2x3]$
M4	$-2.249859550952166 - 0.006928109872329712x1 - 0.49771226494388066x2 - 0.005101177119184265x3 + 0.06000557941356878\mathrm{Log}[x1]^2 + 0.01516927828612444\mathrm{Log}[x1]^3 + 0.0318235538497239\mathrm{Log}[x1]\mathrm{Log}[x2] + 0.013305494068381885\mathrm{Log}[x1]^2\mathrm{Log}[x2] + 0.046691396716127355\mathrm{Log}[x2]^2 - 0.37202181600089496\mathrm{Log}[x1]\mathrm{Log}[x2]^2 + 1.988484276369986\mathrm{Log}[x2]^3 - 0.002636937784545171\mathrm{Log}[x1]\mathrm{Log}[x3] - 0.003194272752963327\mathrm{Log}[x1]^2\mathrm{Log}[x3] + 0.0828072992790462\mathrm{Log}[x2]\mathrm{Log}[x3] + 0.0031250430535352015\mathrm{Log}[x1]\mathrm{Log}[x2]\mathrm{Log}[x3] - 0.4855859352601214\mathrm{Log}[x2]^2\mathrm{Log}[x3] + 0.02895120713558113\mathrm{Log}[x3]^2 - 0.006272112477461329\mathrm{Log}[x1]\mathrm{Log}[x3]^2 + 0.10893889619088801\mathrm{Log}[x2]\mathrm{Log}[x3]^2 + 0.010023936046673607\mathrm{Log}[x3]^3$
M5	$-2.458711767153076 - 4.448482338065852 \times 10^{-132}e^{x1} + 0.0017245963896776709e^{x2} - 8.64591339489585 \times 10^{-100}e^{x3} - 0.0009099999999999999x1x2 - 0.000006986666666666614x1x3 + 0.002323922664004951x2x3 + 0.397288274820158\mathrm{Log}[x1^2] - 0.32541957337757754\mathrm{Log}[x2^2] - 0.11262207004327508\mathrm{Log}[x3^2]$