Many-objecti e Optimisation for An Integrated Supply Chain Management Problem

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Abstract. Due to the complexity of the supply chain with multiple conflicting objectives requiring a search for a set of trade-off solutions, there has been a range of studies applying multi-objective methods. In recent years, there has been a growing interest in the area of many-objective (four or more objectives) optimisation which handles difficulties that multi-objective methods are not able to overcome. In this study, we explore formulation of Supply Chain Management (SCM) problem in terms of the possibility of having conflicting objectives. Non-dominated Sorting Genetic Algorithm-III (NSGA-III) is used as a many-objective algorithm. First, to make an effective search and to reach solutions with better quality, parameters of algorithm are tuned. After parameter tuning, we used NSGA-III at its best performance and tested it on twenty four synthetic and real-world problem instances considering three performance metrics, hypervolume, generational distance and inverted generational distance.

1 Introduction

Supply chain management is critical to achieve sustainable competitive advantage for a company. One major aspect of supply chain management is to select suppliers which can support the success of a company meeting expectations of the company. Another one is to plan and control inventory through the whole network from suppliers to customers, balancing material flows among the entire processes of a supply chain effectively. Thus, supplier selection combined with effective inventory planning has been studied by a number of researchers [5, 7, 9].

In Turk et al. [12], a generic local search meta-heuristic is used to solve the integrated SCM problem which aims to deal with both supplier selection and inventory planning aggregating two objectives subject to several constraints. A simulated annealing approach is applied to the problem balancing the trade-off between supply chain operational cost and supplier risk using two scalarisation approaches, weighted sum and Tchbycheff. That study illustrated the multi-objective nature of the problem testing the proposed approaches on a simple single problem instance. Turk et al. [12] provided an approach which is capable of capturing the trade-off between risk and cost via scalarisation of both objectives.

This gives flexibility to the decision makers to choose from a set of trade-off solutions for supply chain management

In Turk et al. [13], three population based meta-heuristic algorithms are used to tackle the same problem with an attempt to detect the best performing approach. The problem is formulated as a two-objective problem and the performance of three Multi-objective Evolutionary Algorithms (MOEAs), Nondominated Sorting Genetic Algorithm-II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2) and Indicator Based Evolutionary Algorithm (IBEA) are investigated. Although MOEAs performed reasonably well in this study for the two-objective problem, there could be even more conflicting objectives which can be considered in the solution model and then simultaneously optimised. In this problem, the total cost is the sum of 5 different costs, production cost, holding cost, batch cost, transportation cost and stock-out cost, related to production processes. In this study, we treat each cost component as a separate objective and solve the integrated supply chain management problem as a many objective problem using NSGA-III. To the authors' knowledge, this is tone of the first studies in many objective supply chain management problem. The problem takes into account six objectives, i.e, total risk, production cost, holding cost, batch cost, transportation cost and stock-out cost. The main purpose of this paper is to handle multiple optima and other complexities for the integrated problem of supplier selection and inventory planning formulated as a many-objective problem.

The rest of paper is organised as follows. In section II, background information on NSGA-III is provided. In section III, the definition of the problem is reviewed briefly. In section IV, numerical experiments are presented. In section V, computational results are discussed and in section VI, the conclusion and possible directions for future work are given.

2 Preliminaries

This section will provide an introduction to technique that has been used in this work and an overview of related work in the literature.

2.1 Non-dominated Sorting Genetic Algorithm-III

Recently, there has been a growing interest in many-objective (four or more objectives) optimisation problems. Most MOEAs have faced difficulties in solving many-objective optimisation. Difficulties in handling many objectives can be listed as: i) a large fraction of population becomes non-dominated solutions within consideration of the number of objectives, ii) in a large dimensional space, diversity measurement becomes difficult and computationally expensive, iii) recombination operators may be insufficient to improve offspring solutions [2]. Deb and Jain [2] developed a NSGA-II procedure with significant chances in the selection operator to overcome these difficulties and called it NSGA-III.

NSGA-III remains similar to NSGA-II apart from replacing the crowding distance in the selection operator with a systematic evaluation of individuals in the population with respect to the reference points [14]. Initially, a population P_t of size N is randomly generated and then those N individuals are sorted into different non-domination levels. Then, an offspring population Q_t of size N is created applying crossover and mutation operators with associated probabilities (rates). P_t and Q_t are merged to form R_t of size $2N$ which includes elite members of both parent and offspring populations. All individuals in R_t are sorted into a number of non-domination levels such as $F_1; F_2$ and so on. The rest of the NSGA-III algorithm works quite different from NSGA-II. After sorting R_t let us obtain a new population S_t with size N examining individuals in S_t corresponding to a set of reference points either predefined or supplied. All objective values and reference points are first normalised to keep them in an identical range. Then, in order to associate each individual in the population S_t with a reference point, a reference line is determined joining the reference point with the origin of the normalized space. Next, the perpendicular distances between each individual in S_t and their corresponding lines are calculated and each individual is associated to the closest reference line. After that, in order to selectively choose which points will be in the next population P_{t+1}, a niche preserving operator explained in Deb and Jain [2] is used.

2.2 Performance Metrics

The performance of multi-objective algorithms is assessed using various metrics including number of the non-dominated solutions found, distance of the final pareto set to the global pareto-optimal front (accuracy), distribution of the final pareto set with respect to the pareto-optimal front, and spread of the pareto set (diversity) [15, 8]. When dealing with multi-objective optimisation problems, the purpose is to achieve a desirable non-dominated set. However, for a number of reasons, the assessment of results becomes difficult; i) several solutions are generated rather than one like in a single objective optimisation problem, ii) a number of runs need to be performed to assess the performance of EAs due to their stochastic nature, iii) different entities, such as, coverage, diversity of a set of solutions, could be measured and used as a guidance during the search process [10]. In order to handle difficulties, there are several performance metrics proposed in the literature. In this study, three performance metrics, hypervolume (HV), generational distance (GD) and inverted generational distance (IGD) are used (further explanations given in the work of Turk et al. [13]).

In addition, this approach provides a set of trade-off solutions. A common way of (automatically) reducing all trade-off solutions into a 'preferable' reasonable single solution is detecting the solution at the *knee point* on the pareto-front. We have used the method presented in [1] to obtain the a single solution called a knee solution based on the knee point for all problem instances.

Table 1. Notations

Notation	Meaning	Notation	Meaning
i	supplier	p	product
j	manufacturing plant	c	components
k	customer	t	discrete time period

Table 2. Notation for Decision Variables [12]

Variable	Meaning
$P_A(p,j,k,t)$	Amount of product p from plant j to customer k in period t
$C_A(c,i,j,t)$	Amount of component c from supplier i to plant j in period t

3 Problem Description

In Turk et al. [13], a two-stage integrated approach is presented to the supplier selection and inventory planning. In the first stage, in order to get a risk value of each supplier, suppliers are evaluated based on various criteria derived from cost, quality, service and delivery using Interval Type-2 Fuzzy Sets (IT2FSs). In the second stage, the information of supplier rank is fed into an inventory model built to cover the effect of suppliers on the total cost of a supply chain. The integrated SCM problem is formulated as a multi-objective problem which aims to handle two objectives; total cost and total risk. The total cost is the sum of 5 different costs, production cost, holding cost, batch cost, transportation cost and stock-out cost, related to production processes. Due to the existence of conflicting objectives, we treat each cost component as a separate objective and solve the integrated supply chain management problem as a six objective problem using NSGA-III. The formulation of the problem can be found in the work of Turk et al. [13]. In this section, only formulation of each objective is given.

3.1 Problem Formulation

The formulation of six objective supply chain problem is presented below with relevant notation shown in Tables 1, 2 and 3.

In this research, the integrated SCM problem is considered as a six objective problem solved by a many-objective optimisation method. The aim of this study is to minimise: i) potential risk endured TR (Equation 6) as a result of the supplier selection and ii) the each cost of the supply chain THC (Equation 1), TTC (Equation 2), TBC (Equation 3), TPC (Equation 4), TSC (Equation 5).

In Equation 1, the total cost of inventory is shown for the components and products successively. Equation 2 accumulates the transportation cost considering the products in the first row and components in the second row, respectively. In Equation 3, the component order and setup costs as batch costs are added. The manufacturing and shortage costs for each product and each component are included in Equation 4 as a total production cost. The stock-out cost is depicted

Table 3. Notation used for the formulation of the problem [12]

Notation	Meaning
$P_I(p, j, t)$	Inventory of product p at plant j in period t
$C_I(c, j, t)$	Inventory of component c at plant j in period t
$Y_P(p, k)$	Product p's selling price for customer k
$T_C(c, i, j)$	Carrying cost for component c between supplier i and plant j
$T_P(p, j, k)$	Carrying cost for product p between plant j and customer k
$I_C(c, j)$	Component c's inventory cost at plant j
$I_P(p, j)$	Product p's inventory cost at plant j
$S_C(c, j)$	Shortage cost at plant j for component c
$S_P(p, j)$	Shortage cost at plant j for product p
$O_C(c, i)$	Ordering cost of supplier i for component c
$M_P(p, j)$	Manufacturing cost for product p at plant j
$S(p, j)$	Setup cost in plant j for product p
$D_S(i, j)$	Distance between supplier i and plant j
$D_P(j, k)$	Distance between plant j and customer k
$Rank(i)$	Rank of vendor i
$Risk(i)$	Risk of vendor i
$P_M(p, k, t)$	Non-fulfilment amount of product p for customer k in period t

in Equation 5 as a penalty cost incurred when the quantity of production does not satisfy the customer demands.

$$\textit{minimise } THC = \sum_t \left(\sum_p \sum_j I_P(p;j) \times P_I(p;j;t) + \sum_c \sum_j I_C(c;j) \times C_I(c;k;t) \right) \tag{1}$$

$$\begin{aligned}\textit{minimise } TTC = \sum_t \Bigg(& \sum_p \sum_j \sum_k \left(P_A(p;j;k;t) \times D_P(j;k) \times T_P(p;j;k) \right) \\ & + \sum_c \sum_i \sum_j \left(C_A(c;i;j;t) \times D_S(i;j) \times T_C(c;i;j) \right) \Bigg)\end{aligned} \tag{2}$$

$$\begin{aligned}\textit{minimise } TBC = \sum_t \Bigg(& \sum_c \sum_i \sum_j O_C(c;i) \times C_A(c;i;j;t) \\ & + \sum_p \sum_j \sum_k S(p;j) \times P_A(p;j;k;t) \Bigg)\end{aligned} \tag{3}$$

$$\begin{aligned}\textit{minimise } TPC = \sum_t \Bigg(& \sum_p \sum_j \sum_k M_P(p;j) \times P_A(p;j;k;t) \\ & + \sum_p \sum_j S_P(p;j) \times P_I(p;j;t) + \sum_c \sum_j S_C(c;j) \times C_I(c;j;t) \Bigg)\end{aligned} \tag{4}$$

$$\textit{minimise } TSC = \sum_t \left(\sum_p \sum_k P_M(p;k;t) Y_P(p;k) \right) \tag{5}$$

$$minimise\ TR = \sum_t \sum_c \sum_i \sum_j C_A(c; i; j; t) \times Risk(i) \quad (6)$$

Equation 6 demonstrates the total risk of suppliers with respect to Equation 7 which shows the calculation of a coefficient for the risk of each supplier by normalising the supplier rank (detailed in Turk et al. [13]).

$$Risk(i) = \frac{\sum_i Rank(i)}{Rank(i)} \quad (7)$$

4 Preliminary Experiments

4.1 Experimental Setup

The results found in stage one is carried to the second stage to solve the integrated problem using NSGA-III. The Jmetal suite [4, 3] is used to run all experiments with NSGA-III as a many-objective evolutionary algorithm. Each trial is repeated for 30 times during the experiments, where each run yields a set of trade-off solutions. A run *terminates* whenever 5000 iterations/generations are exceeded.

The same *chromosome representation* explained in Turk et al. [13] is used to depict a potential inventory plan. *The initial population* is generated randomly. A binary tournament selection is employed to create a offspring population. Simulated Binary *Crossover* (SBX) and Polynomial *Mutation* operators are used. The parameters of NSGA-III include the *population size* (P), *crossover probability* (P_c), *distribution index for crossover* (D_m), *distribution index for mutation* (D_c) and *number of divisions* (N_d). NSGA-III has the same algorithmic control parameters as NSGA-II, including *number of divisions* (N_d). The number of divisions is utilised to determine how many reference points will be used in a reference line to maintain diversity in obtained solutions. All the algorithmic control parameters are tuned.

4.2 Problem Instances

Twenty four problem instances provided by Turk et al. [13] are used in this study. Problem instances have different characteristics and sizes, where four of them are real world problem instances and 20 of them are randomly generated based on those instances.

4.3 Parameter Tuning of NSGA-III

Parameters of NSGA-III are tuned using Taguchi orthogonal arrays [11] as a design of experiments method. We investigated five control parameters for NSGA-III with the following potential settings: $P \in \{25, 50, 100, 200\}$, $P_c \in$

Table 4. Average rank of NSGA-III, with a particular parameter configuration based on the L^{16} Taguchi orthogonal array

Experiment number (EN)	P	P_c	D_c	D_m	N_d	Average Rank NSGA-III	EN	P	P_c	D_c	D_m	N_d	Average Rank NSGA-III
1	25	0.6	5	5	3	13.4	9	100	0.6	15	20	4	11.4
2	25	0.7	10	10	4	8.9	10	100	0.7	20	15	3	14.0
3	25	0.8	15	15	5	6.4	11	100	0.8	5	10	6	4.0
4	25	0.9	20	20	6	5.2	12	100	0.9	10	5	5	5.9
5	50	0.6	10	15	6	4.2	13	200	0.6	20	10	5	5.6
6	50	0.7	5	20	5	6.8	14	200	0.7	15	5	6	3.0
7	50	0.8	20	5	4	9.4	15	200	0.8	10	20	3	14.2
8	50	0.9	15	10	3	13.5	16	200	0.9	5	15	4	10.2

Table 5. ANOVA test results for dismissing the contribution of each parameter for NSGA-III in terms of percent contribution

MOEAs	P	P_c	D_c	D_m	N_d	$Error$	Total
NSGA-III	0.28	0.28	0.11	2.51	96.81	-	100 %

{0.6,0.7,0.8,0.9}, D_c, $D_m \in \{5, 10, 15, 20\}$ and $N_d \in \{3, 4, 5, 6\}$. The L^{16} Taguchi orthogonal arrays design is used to achieve the best parameter configuration. We followed the same way explained in Turk et al. [13] and obtained results as shown in Table 4.

The mean effect of each parameter is calculated in the same manner as explained in the work of Turk et al. [13]. Figure 1 provides the main effects plot indicating the performance of each parameter value setting. The best configuration for NSGA-III is attained as 200 for P, 0.7 for P_c, 10 for D_c, 5 for D_m and 6 for N_d. In addition, the contribution of each parameter setting on the performance of NSGA-III is analysed using ANOVA. Table 5 summarises the results. The number of divisions has a significant contribution within a confidence level of 95% on the performance of NSGA-III. In the same manner, hypervolume of three selected instances is used to assess the performance of each parameter setting configured based on the Taguchi method.

5 Computational Results

Given six objective functions, the experimentation is conducted in exactly the same manner as when generating a Pareto set of solutions with two objectives as explained in Turk et al. [13]. NSGA-III is applied to 24 problem instances. The high-dimensional trade-off front in a many-objective evolutionary algorithm is analysed. Three different performance metrics and its cost results are considered to investigate its performance. In order to tackle difficulties of the high-dimensional trade-off front for the six objective problem, we aggregate all cost

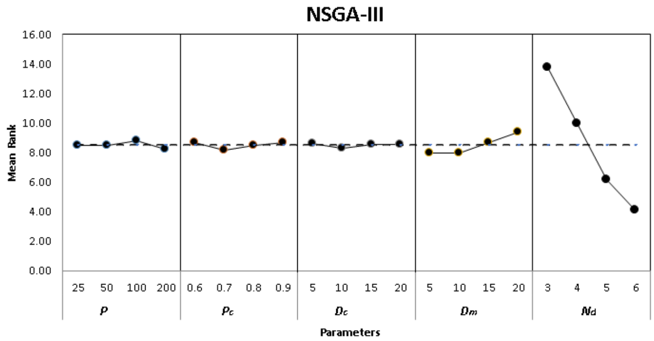

Fig. 1. Main effects plot with mean rank values in NSGA-III

values together and evaluated them same as the two objective problem (to find pareto-front sets and its performance). For 24 instances, NSGA-III provides better mean values of hypervolume, generational distance and inverted generational distance than NSGA-II, SPEA 2 and IBEA in Turk et al. [13].

Six objectives, total risk, total production cost, total holding cost, total batch cost, total transportation cost and total stock-out cost computed for each knee solution to each instance are summarised in Table 7. We have observed that NSGA-III achieved knee solutions for the majority of the instances with a low customer satisfaction rate. To find reasons for poor levels of customer service and to visualise relationship among objectives, Figure 2 depicts the pareto optimal set of Inst19 as an example in 'parallel coordinates' [6] generated by using NSGA-III. Each green line represents a pareto optimal solution and indicates change through objectives from one to another. The black line shows the knee solution for Inst19. Figure 3 displays the same data set but this time, there are two lines and each line represents a single solution in the pareto set of Inst19. In Figure 3, the solution 1 with a high risk has low production and stock-out costs while the solution 2 represents low risk scenario with high production and stock-out costs. Also, the high risk solution consists of relatively low holding cost. Moreover, from the visualisation, we can observe that there is obvious inverse-correlation between the transportation cost and holding cost as seen in Figure 2. In this sense, decreasing the holding cost will increase transportation cost. However, the correlation between other objectives is not quite as obvious. Therefore, the relationship between risk and each cost is investigated in Figure 4. There is no specific relationship between risk and production cost, transportation cost and batch cost. It is obviously seen that there is negative relationship between risk and holding cost, and between risk and stock-out cost.

In summary, we have explored the performance of NSGA-III, in the six objective integrated SCM problem. Based on performance metrics, NSGA-III performed reasonably well in this study. However, the empirical results indicate that NSGA-III did not achieve high quality trade-off solutions satisfying at least

Table 6. Performance of NSGA-III in terms of hypervolume (HV), generational distance (GD) and inverted generational distance (IGD)

Inst.		HV	GD	IGD	Inst.		HV	GD	IGD
Inst1	Mean	0.8617	14,191.2	465,424.7	Inst13	Mean	0.9206	76,152.2	713,037.7
	Stnd.	0.0178	12,478.6	178,732.2		Stnd.	0.0088	41,477.9	279,123.7
Inst2	Mean	0.9026	20,818.4	165,035.9	Inst14	Mean	0.8746	79,809.1	212,990.4
	Stnd.	0.0070	9,786.4	55,906.3		Stnd.	0.0100	34,490.0	57,665.8
Inst3	Mean	0.8263	46,785.9	2,189,103.3	Inst15	Mean	0.9263	94,034.5	204,205.7
	Stnd.	0.0084	19,769.8	1,026,613.6		Stnd.	0.0074	46,892.7	57,232.2
Inst4	Mean	0.8383	30,252.1	457,079.3	Inst16	Mean	0.8980	90,109.0	182,753.4
	Stnd.	0.0102	23,904.7	271,723.8		Stnd.	0.0070	44,550.3	53,838.6
Inst5	Mean	0.8971	46,179.5	298,860.6	Inst17	Mean	0.8862	115,584.6	534,597.3
	Stnd.	0.0091	29,988.4	127,470.0		Stnd.	0.0120	64,992.4	190,702.7
Inst6	Mean	0.8693	58,723.5	396,973.3	Inst18	Mean	0.9083	131,657.6	209,729.7
	Stnd.	0.0045	28,026.6	149,382.0		Stnd.	0.0110	70,231.8	45,540.7
Inst7	Mean	0.8770	51,260.7	168,246.7	Inst19	Mean	0.9837	43,111.0	247,124.0
	Stnd.	0.0078	24,129.5	34,780.2		Stnd.	0.0016	19,239.8	72,672.2
Inst8	Mean	0.8717	19,298.9	85,388.1	Inst20	Mean	0.9792	117,175.2	301,284.0
	Stnd.	0.0060	11,332.0	19,731.9		Stnd.	0.0026	51,612.7	65,545.4
Inst9	Mean	0.8899	118,589.7	199,444.9	Inst21	Mean	0.9847	57,679.7	307,158.7
	Stnd.	0.0153	122,349.9	136,917.6		Stnd.	0.0017	17,709.2	92,594.1
Inst10	Mean	0.8731	31,074.0	141,270.7	Inst22	Mean	0.9862	67,881.1	229,310.3
	Stnd.	0.0078	11,447.5	41,997.4		Stnd.	0.0013	29,465.3	58,393.4
Inst11	Mean	0.8630	61,447.7	162,999.2	Inst23	Mean	0.9886	47,219.0	179,730.0
	Stnd.	0.0077	65,245.3	47,410.7		Stnd.	0.0007	13,601.8	49,710.5
Inst12	Mean	0.8802	82,517.8	233,954.7	Inst24	Mean	0.9852	75,444.5	261,063.7
	Stnd.	0.0082	44,704.8	73,336.6		Stnd.	0.0014	30,343.3	58,524.4

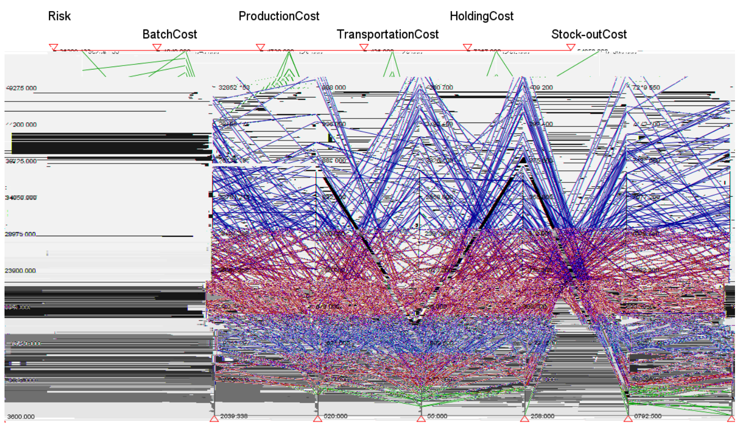

Fig. 2. Results of NSGA-III in parallel coordinate for Inst19; green lines show trade-off solutions among objectives and black line indicates the knee solution.

90% of the customer demand while each cost is considered as an objective. In addition, to investigate conflicting objectives, the parallel coordinates figures are used visualising the relationship among objectives. It is observed that there is an obvious relationship between some objectives such as risk and stock-out cost.

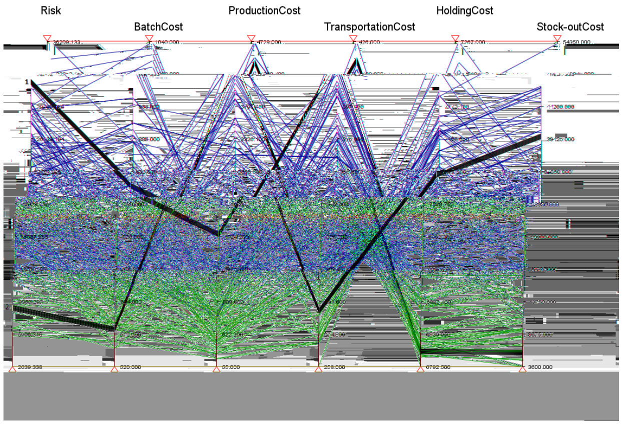

Fig. 3. Two solutions of NSGA-III highlighted in parallel coordinate; Trade-off among objectives for Inst19

Table 7. Objective wise results of NSGA-III. TR: Total Risk, TC: Total Cost, TBC: Total Batch Cost, TPC: Total Production Cost, TTC: Total Transportation Cost, TSC: Total Stock-out Cost, THC: Total Holding Cost.

Inst.	TR	TC	Service Level	TBC	TPC	TTC	TSC	THC
Inst1	10,875.0	3,120.0	83.97%	330.0	2,100.0	190.0	0.0	500.0
Inst2	7,554.3	3,812.3	85.68%	300.0	879.0	176.2	1,911.1	546.0
Inst3	7,394.3	4,189.4	78.02%	270.0	1,426.6	166.8	1,405.0	921.0
Inst4	10,398.8	4,667.7	69.45%	270.0	1,643.5	192.2	1,136.1	1,425.9
Inst5	1,814.0	5,768.6	46.81%	200.0	703.0	122.9	1,674.5	3,068.2
Inst6	9,052.5	5,133.9	83.91%	230.0	2,111.6	182.7	1,783.7	826.0
Inst7	15,108.8	6,332.5	61.78%	490.0	2,220.0	269.0	933.5	2,420.0
Inst8	21,172.1	5,480.9	80.29%	700.0	2,524.2	307.9	868.6	1,080.3
Inst9	15,617.4	4,741.2	80.25%	680.0	1,963.0	302.5	859.5	936.3
Inst10	16,217.0	5,872.8	57.83%	600.0	1,695.1	267.1	834.1	2,476.4
Inst11	19,834.3	6,005.7	76.31%	710.0	3,089.6	322.9	460.4	1,422.8
Inst12	11,343.0	8,720.8	67.07%	480.0	4,023.6	243.7	1,101.3	2,872.1
Inst13	11,051.8	7,043.5	55.21%	390.0	1,460.0	281.0	1,757.5	3,155.0
Inst14	17,517.9	7,601.5	66.56%	540.0	2,679.9	285.5	1,554.2	2,541.9
Inst15	8,401.4	6,595.7	59.07%	480.0	1,404.1	238.1	1,774.0	2,699.5
Inst16	11,969.5	6,430.6	64.05%	460.0	1,748.5	300.7	1,609.3	2,312.1
Inst17	12,135.5	9,952.9	60.74%	480.0	3,554.5	290.0	1,721.3	3,907.1
Inst18	6,130.3	7,093.1	51.47%	410.0	1,250.1	247.0	1,743.8	3,442.2
Inst19	16,688.4	10,312.5	83.42%	680.0	690.0	348.0	6,884.5	1,710.0
Inst20	24,902.3	11,994.0	79.19%	970.0	1,657.1	442.6	6,427.7	2,496.5
Inst21	16,885.4	11,549.7	83.39%	830.0	1,380.8	365.9	7,054.8	1,918.2
Inst22	22,838.1	10,990.0	93.93%	1,090.0	1,715.7	365.4	7,152.3	666.6
Inst23	15,405.6	9,925.7	99.53%	890.0	1,121.2	358.4	7,509.5	46.5
Inst24	23,212.4	9,713.2	91.88%	1,020.0	829.9	417.1	6,657.8	788.4

Objective reduction can be alternative way removing the redundant objectives in the original objective set. To improve performance and to achieve acceptable cost results, some objectives might be excluded and the problem will be solved again. Also the model can be improved to reduce the stock-out cost.

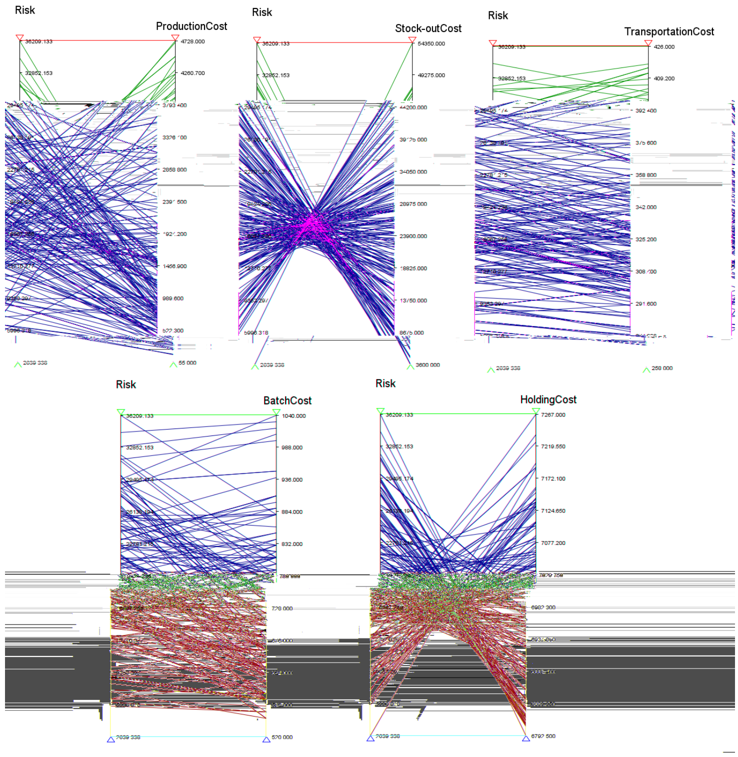

Fig. 4. Risk vs Cost objectives' results of NSGA-III in parallel coordinate for Inst19

6 Conclusions

This paper provides an investigation of meta-heuristic algorithm, NSGA-III on the integrated SCM problem as one of the first studies in literature. Also, this chapter analysed performance of NSGA-III using three well known performance metrics. First, the optimal parameter setting is found for the algorithm. After tuning, the algorithm is tested on twenty four problem instances. The results show the overall success of NSGA-III comparing to NSGA-II given in Turk et al. [13]. Moreover, we examine the trade-off between all contributing costs to the total cost and risk, separately. The many-objective optimisation algorithm, NSGA-III is applied to the six objective formulation of the same problem [13]. NSGA-III performs well over all instances. However, it is found that NSGA-III cannot satisfy customer expectations while producing high stock-out cost. Based on these findings, the number of objectives would be reduced to four for many-objective optimisation based on relationships among objectives found as in the parallel coordinates figures. Another future study could be applying the approach to new unseen instances possibly even larger than the ones used in this study and/or changing the decision makers' supplier related preferences creating more instances.

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