Optimization of A Five-Echelon Supply Chain Network using Particle Swarm Intelligence Algorithms

V. R. Sathish Kumar, S. P. Anbuudayasankar

***Abstract*: Technology has shrunk the global markets and information is accessible very quickly and effortlessly. Business organizations world over concentrate on their production systems to improve the quality of the end product, well distribute the product and optimize cost of resources. Transportation cost, inventory carrying cost and shortage costs constitute the major costs in cost of distribution. A competent supply chain always strives to manufacture the right quantity of end products and hold a minimum inventory across the entire supply chain. In thecurrent paper, a five echelon supply chain model is developed and it is optimized using particle swarm intelligence algorithm.**

***Index Terms*: Particle swarm intelligence algorithm, Supply chain management.**

I. INTRODUCTION

Evolution of internet technologies has shrunk the world and info is open and accessible very easily. Business organizations (BO) globally are experiencing stiff competition within an industry. Companies are drifting from customer satisfaction to customer delight by enhancing product quality and incorporating unique customizable product features. Cost of raw material, labor, power and other manufacturing inputs are rather open, so BOs concentrate on process improvement to optimize resource utilization and its associated cost. Cost of distribution (COD) usually ranges from 2.9 % to 8.9% of sales value, which majorly includes transportation of raw material, components, work-in-progress and finished goods, carrying cost of excess inventory in the supply chain (SC) and shortage cost [1]. In recent years, countries world over are emphasizing on industries and society to adopt technology that yield green manufacturing systems. Sustainability of green technology is so much wrapped around financials of an individual BO, which again points towards efficient utilization of resources. Inventory is a current asset figuring in the balance sheet; inventory helps improve business volume and bottom line of BO, but all this when maintained at optimal levels. High inventory levels among members of SC erodes the profit as interest on locked up capital, opportunity of capital not being able to use elsewhere, maintenance of inventory, and other related costs [2]. Whereas a low inventory, results in shortage of product to sales, dent in the goodwill or brand image, perception of customer towards the retailer and brand and the like. Optimal inventory calls for a very well-established communication among members of SC. Transportation cost account for 71% of COD apart from impacting the environment. Industry and researchers are continuously working towards developing models to minimize the emission from fossil fuel used by transportation sector [3]. This paper aims developing a model that strikes a balance among transportation cost (TC), inventory carrying cost (CC) and shortage cost (ShC) by employing vehicles of varying capacity to manage optimal inventory in the SC.

II. LITERATURE SURVEY

Swift changes in environment, technology and market has warranted BO to maximize the performance of all the member of SC rather than an individual member. To mitigate this situation, SC members ought to establish strong long term relationship to leverage information and resources. Which results in minimizing and sharing risks [4], reduce product development cost, reduce logistics cost, improve productivity, reduce inventory across SC, access scarce resources, improve quality and lot more. Internet based information and communication technology has helped to share real time info among members of SC to optimally use the resources and value creation [5]. SC policy is very crucial for success of any BO. Well defined SC objective(s) ought to lead the SC approach, which forms the fundamental driver of tactical decision making and align all individual goals to the organizations' [6]. Strategic decision must be imbibed into the SC right in the initial stage, with both internal and external customer satisfaction as the core objective [7]. Cost of distribution (COD) and time to supply are most frequently used performance evaluation metrics of a SC model [8]. COD is the collection of transportation cost, inventory carrying cost and shortage cost. Primary objective of any SC is minimization of all associated costs; which is the result of low or optimal inventory level retained through all echelons [9]. Optimal or minimum inventory ease costs and surfaces out any hidden problems at very early period of time. SC develops a clear understanding and helps serve better the dynamic changing requirements and demands of customer [10]. SC members ougth to be more swift and reliable to satisfy end user demands which is usually at the lowest echelon. This will warrant an open and transparent intra and inter departmental

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communication. [1]. Just-in-time production system adopted by many companies is a remarkable illustration of reliable SC which helped reduce the CC. TC at initial stages would seem high, to maintain a low inventory levels across all echelons but is justifiable with the benefits and would continuously optimize in long term [11]. In current scenario, industries are using the resources optimally for cost computation and enhancing its profit margins. [12]. Researchers working on resource optimization deploy various evolutionary algorithms that mimic nature. Particle swarm intelligence optimization (PSO) is an evolutionary algorithm developed by Eberhart and Kennedy in 1995 that mimics the behavior of swarm of birds or school of fish. Sathish Kumar et al. (2018) developed a three echelon SCM using goal programming and used PSO to optimize the resources [14]. PSO explores and exploits the solution space thoroughly very efficiently that it is usually employed to solve problems of complex nature [13]. PSO works on its own cognitive behavior and shared social behavior of swarm.

III. PROBLEM DEFINITION AND SC MODEL

Advent of internet technology has made the costing of products more transparent. Rich information available to customer has made them rational in their decisions and is not willing to pay more. Costing is one major area that companies often try breaking their own benchmark. Current study consists of a five echelon SC model consisting of component or assembly or sub-assembly supplier, end product manufacturing plant, warehouse, distributor and retailer. Transportation of components, assemblies, sub-assemblies and end product between the members of SC is facilitated by a third party logistic service provider (3PLSP). 3PLSP maintains three types of vehicles with varying capacities in terms of consignment load. Cost reduction can be achieved by matching the vehicle capacity with the consignment load and cancelling trips with consignment loads less than 75% capacity of vehicle. Excess inventory attracts holding or carrying cost and cost of capital, but holding fewer inventories runs the risk of stock-out situation and its related cost. This model handles varied demand scenarios and in each scenario, it optimizes these costs.

IV. OPTIMIZATION OF MULTI-OBJECTIVE FIVE ECHELON SC ARCHITECTURE USING PSO ALGORITHMS

A. *Intro to PSO algorithm*

Particle swarm optimization (PSO) is an evolutionary algorithm mimicking school of fish randomly searching for food. PSO is initialized with a random number of particles to search the entire solution space. First part in the equation 1, is the product of velocity of n^{th} particle and inertia weight of the same particle. A large inertia weight ensures particles to widely explore the solution space and a smaller one confines the particle to a local solution space. Second part of the same equation, represents the cognitive part, which orients the n^{th} particle towards the best previous position it had held in earlier iterations. Third component represents the social part, where the particle n orients towards the best previous positions held by any of the particle of the swarm in the earlier iterations. Constants C1 and C2 are the learning factors and can take a maximum value of 2. In the initial iterations, learning factors of both cognitive and social component are maintained at lower levels because it would not have explored the solution space enough to identify P_{best} and G_{best}.

B. *Linearly decreasing inertia weight particle swarm optimization algorithm equations (LDIW-PSO)*

$$v_{n+1} = \omega_n v_n + C_1[r_1(P_{best} - X_n)] + C_2[r_2(G_{best} - X_n)] \quad (1)$$

$$\omega = \left[\omega_{\max} - \frac{\omega_{\max} - \omega_{\min}}{iter_{\max}} * iter\right] \quad (2)$$

$$X_{n+1} = X_n + v_{n+1} \quad (3)$$

C. *Global – local best inertia weight particle swarm optimization algorithm equations (GLBIW-PSO)*

$$v_{n+1} = \omega_n v_n + C_1[r_1(P_{best} - X_n)] + C_2[r_2(G_{best} - X_n)] \quad (4)$$

$$\omega = \left(1.1 - \frac{G_{best}}{P_{best}}\right) \quad (5)$$

$$X_{n+1} = X_n + v_{n+1} \quad (6)$$

D. *Mathematical Model*

$X_{c,s,p}$	Quantity of component 'c' supplied by supplier 's' to plant 'p'
$Rn_{v,s}$	Rent for vehicle 'v' used to transport parts from supplier 's'
TOQ_e	Total order quantity of end product 'e'
$CO_{e,o}$	Confirmed order of end product 'e' by OEM 'o'
FD_e	Forecasted demand of end product 'e'
$Dem_{e,p}$	Demand of end product 'e' from plant 'p'
$Cap_{e,p}$	Capacity of plant 'p' to manufacture end product 'e'
Wt_c	Weight of a unit of component 'c'
$V_{v,s}$	Vehicle 'v' used to transport components from supplier 's'
$B_{v,s}$	Boolean variable if vehicle of type 'v' is used to transport components from supplier 's'

$LP_{v,s}$	Load penalty for vehicle of type $'v'$ is used to transport components from supplier $'s'$
$Y_{e,p,w}$	Quantity of end product $'e'$ supplied from plant $'p'$ to warehouse $'w'$
$Inv_{e,r}$	Inventory of end product $'e'$ held with retailer $'r'$
$Cc_{e,p}$	Carrying cost per unit of end product $'e'$ in plant $'p'$ per time period
$Sh_{e,w}$	Shortage cost per unit of end product $'e'$ in warehouse $'w'$
$Q_{c,s}$	Quantity of excess inventory of component $'c'$ held with supplier $'s'$
$Cap_{e,p}$	Capacity of plant $'p'$ to manufacture end product $'e'$

$$Min\ Z_R = (Rn_{v,s} + LP_{v,s})B_{v,s} + (Rn_{v,p} + LP_{v,p})B_{v,p} + (Rn_{v,w} + LP_{v,w})B_{v,p} + (Rn_{v,di} + LP_{v,di})B_{v,di} \quad \forall (v,s),(v,p),(v,w),(v,di) \qquad (7)$$

$$Min \quad Z_C = \sum_{c,s} Q_{c,s}Cc_{c,s} + \sum_{e,p} Q_{e,p}Cc_{e,p} + \sum_{e,w} Q_{e,w}Cc_{e,w} + \sum_{e,r} Q_{e,r}Cc_{e,r} \qquad (8)$$

$$Min \quad Z_{Sh} = \sum_{c,s} Q_{c,s}Sh_{c,s} + \sum_{e,p} Q_{e,p}Sh_{e,p} + \sum_{e,w} Q_{e,w}Sh_{e,w} + \sum_{e,w} Q_{e,w}Sh_{e,w} + \sum_{e,r} Q_{e,r}Sh_{e,r} \qquad (9)$$

$$TOQ_e \le \left[\sum_{o} CO_{e,o} + FD_e\right] \quad \forall e \qquad (10)$$

$$Dem_{e,p} \le \frac{Cap_{e,p}}{\sum_{p} Cap_{e,p}} \quad TOQ_e \quad \forall e,p \qquad (11)$$

$$\sum_{e} Cap_{e,p} \le Cap_p \quad \forall p \qquad (12)$$

$$\sum_{p} Dem_{e,p} \le TOQ_e \quad \forall e \qquad (13)$$

$$TOQ_c \le N_{c,e}\ TOQ_e\ \forall c,e \qquad (14)$$

$$Dem_{c,s} \le \frac{Cap_{c,s}}{\sum_{s} Cap_{c,s}} \quad TOQ_c \quad \forall c \qquad (15)$$

$$\sum_{s} Dem_{c,s} \le TOQ_c \quad \forall c \qquad (16)$$

$$\sum_{c} Cap_{c,s} \le Cap_s \quad \forall s \qquad (17)$$

$$\sum_{p} X_{c,s,p} \le Dem_{c,s} \quad \forall c,s \qquad (18)$$

$$L_{v,s} = \sum_{p}\sum_{c} (X_{c,s,p}\ Wt_c) - V_{v,s}\ \forall v,s \qquad (19)$$

$$B_{v,s} = 1\ if\ \min(L_{v,s} > 80\%\ of\ V_{v,s})\ \forall v,s \qquad (20)$$

$$B_{v,s} = 0\ if\ \min(L_{v,s} \le 80\%\ of\ V_{v,s})\ \forall v,s \qquad (21)$$

$$LP_{v,s} = \frac{(L_{v,s}\ B_{v,s})\ LPC}{V_{v,s}} \forall v,s \qquad (22)$$

$$Q_{c,s} = \left[(U_{s,c}\ Cap_{s,c}) + Inv_{c,s} - X_{c,s,p}\right] \quad \forall c,s \qquad (23)$$

$$L_{v,p} = \sum_{w}\sum_{e} (Y_{e,p,w}\ Wt_e) - V_{v,p}\ \forall v,p \qquad (24)$$

$$B_{v,p} = 1\ if\ \min(L_{v,s} > 80\%\ of\ V_{v,p}) \quad \forall v,p \qquad (25)$$

$$B_{v,p} = 0\ if\ \min(L_{v,p} \le 80\%\ of\ V_{v,p}) \quad \forall v,p \qquad (26)$$

$$LP_{v,p} = \frac{(L_{v,p}\ B_{v,p})\ LPC}{V_{v,p}} \forall v,p \qquad (27)$$

$$Q_{e,p} = \left[(U_{p,e}\ Cap_{p,e}) + Inv_{e,p} - Y_{e,p,w}\right] \quad \forall e,p \qquad (28)$$

$$L_{v,w} = \sum_{w}\sum_{e} (Y_{e,w,d}\ Wt_e) - V_{v,w}\ \forall v,w \qquad (29)$$

$$B_{v,w} = 1 \ if \ \min(L_{v,w} \ > 80\% \ of \ V_{v,p}) \quad \forall v, w \qquad (30)$$

$$B_{v,w} = 0 \ if \ \min(L_{v,w} \ \leq 80\% \ of \ V_{v,p}) \quad \forall v, w \qquad (31)$$

$$LP_{v,w} = \frac{(L_{v,w} \ B_{v,w}) \ LPC}{V_{v,w}} \forall v, w \qquad (32)$$

$$\sum_p Y_{e,p,w} - \sum_d Y_{e,w,d} + Inv_{e,w} \leq Cap_{e,w} \quad \forall \quad e, w \qquad (33)$$

$$Q_{e,w} = \left[\left(\sum_p Y_{e,p,w} - \sum_d Y_{e,w,d}\right) + Inv_{e,w} - Y_{e,p,w}\right] \quad \forall e, w \qquad (34)$$

$$L_{v,di} = \sum_d \sum_e (Y_{e,di,r} \ Wt_e) - V_{v,di} \ \forall v, di \qquad (35)$$

$$B_{v,di} = 1 \ if \ \min(L_{v,di} \ > 80\% \ of \ V_{v,di}) \quad \forall v, di \qquad (36)$$

$$B_{v,di} = 0 \ if \ \min(L_{v,di} \ \leq 80\% \ of \ V_{v,di}) \quad \forall v, di \qquad (37)$$

$$LP_{v,di} = \frac{(L_{v,di} \ B_{v,di}) \ LPC}{V_{v,di}} \forall v, di \qquad (38)$$

$$\sum_p Y_{e,p,w} - \sum_d Y_{e,w,d} + Inv_{e,w} \leq Cap_{e,w} \quad \forall \quad e, w \qquad (39)$$

$$Q_{e,w} = \left[\left(\sum_p Y_{e,p,w} - \sum_d Y_{e,w,d}\right) + Inv_{e,w} - Y_{e,p,w}\right] \quad \forall e, w \qquad (40)$$

$$Inv_{e,r} + \sum_p Y_{e,di,r} - Sal_{e,r} \leq Cap_{e,r} \forall \quad e, r \qquad (41)$$

$$Q_{e,r} = Inv_{e,r} + Y_{e,di,r} - Sal_{e,r} \leq Cap_{e,r} \forall e, r \qquad (42)$$

Equations (7) strive to minimize the transportation cost by imposing a penalty whenever a trip is underutilized. Equation (8) and (9) minimizes the inventory carrying cost and shortage cost respectively. Equations (10) to (18) ensure the demand of end product is distributed among the plants based on their capacities. Load penalty for underutilized trips are computed in equation (19) till (22). Excess inventory among suppliers are computed in equation (23). Load penalty for underutilized trips from plants to warehouse is computed in equations (24) to (27). Inventory at plants is computed at the warehouse through equation (28). Type of vehicle selection based on capacity of vehicle and weight of consignment to be transported from warehouse, is done through equations (29) to (32). End product inventory at warehouse is ascertained through equations (33) and (34). Equations (35) till (38) compute the load penalty for underutilized trips from distributor to retailer. Equation (39) and (41) ensures quantity of end products are within the capacities of the warehouse and distributor. Equations (40) and (42) compute the inventory levels at warehouses and distributors.

V. RESULTS AND DISCUSSIONS

The five echelon SC model handles the COD, which majorly constitutes the TC CC and ShC. The SC model is a multi-objective model minimizing TC, CC and ShC. Though all the three are visibly a minimization problem on the surface, they are conflicting when analyzed deeply. Transportation cost increases when the trips are more frequent, resulting in bring down the carrying cost and shortage cost. In similar lines, when members of SC prefer to carry more inventories pushing the CC high, the instance of members running out of product is low. On every occasion when dimensions of a multi-objective problem increases, so as the complexity of the solution space and solutions. The SC model developed is optimized using LDIW and GLBIW PSO variants. Twenty scenarios with demand varying from 50 to 100 units of end products were developed and TC, CC and ShC were determined using LDIW and GLBIW PSO variants to compute the inertia weight. Each demand scenario is replicated 10 times and the

Table 1 Performance of PSO algorithm using LDIW inertia weight

DS	TC Best	TC Worst	TC Mean	TC SD	CC Best	CC Worst	CC Mean	CC SD	ShC Best	ShC Worst	ShC Mean	ShC SD	Best COD	Worst COD
1	1361282	1558283	1511535	41762	167201	254579	246942	7561	14636	17621	16740	328	1543119	1830483
2	1337498	1551689	1489621	40499	187550	232418	218473	6508	14223	16771	15932	247	1539271	1800878
3	1532637	1632100	1534174	48637	178587	223690	216979	6733	14186	16543	15716	324	1725410	1872333
4	1379868	1535828	1443678	43925	240536	289631	278046	6834	16748	18102	17559	273	1637152	1843561
5	1321058	1386310	1316995	39371	251698	262310	254441	7371	14215	17518	16992	236	1586971	1666138
6	1389500	1515438	1439666	40311	282856	287821	273430	8711	14329	18617	17872	309	1686685	1821876
7	1323148	1480924	1392069	42651	217545	250542	238015	6740	14681	17168	16481	276	1555374	1748634
8	1237967	1458406	1385486	40690	224981	245068	237716	6813	16316	16701	15866	284	1479264	1720175
9	1377824	1621134	1556289	41015	233504	236780	224941	7037	14216	18620	17875	331	1625544	1876534
10	1318819	1729863	1677967	47917	250458	255427	245210	6122	15449	17904	16830	354	1584726	2003194
11	1412703	1696224	1645337	42834	199791	223507	212332	5650	13861	16538	15546	308	1626355	1936269
12	1209085	1493183	1433456	41212	243204	290406	281694	6450	16092	16531	15539	301	1468381	1800120
13	1391925	1721703	1652835	43903	182797	281007	264147	8009	15224	18199	17289	257	1589946	2020909
14	1207319	1615417	1518492	47655	208554	216264	205451	6120	15438	17433	16736	239	1431311	1849114
15	1368195	1701015	1649985	54432	197013	306912	291566	8594	16001	16376	15885	241	1581209	2024303
16	1305650	1673239	1572845	46683	258137	271313	257747	8004	14446	18316	17583	330	1578233	1962868
17	1336134	1413793	1357241	38879	246473	262551	254674	7594	15865	16631	16132	319	1598472	1692975
18	1372049	1734871	1648127	49097	224282	240454	233240	6733	15464	16743	16241	263	1611795	1992068
19	1389857	1582162	1518876	45092	201168	219440	210662	6627	13331	17856	17142	262	1604356	1819458
20	1293975	1485358	1440797	47234	192395	203511	197406	5922	16165	18764	18201	411	1502535	1707633

Table 2 Performance of PSO algorithm using GLBIW inertia weight

DS	TC Best	TC Worst	TC Mean	TC SD	CC Best	CC Worst	CC Mean	CC SD	ShC Best	ShC Worst	ShC Mean	ShC SD	Best COD	Worst COD
1	1009165	1446806	1417870	43549	134613	138666	133119	4105	10670	16602	16436	244	1154448	1602074
2	1166214	1437582	1408830	39102	111458	155062	147309	4094	16771	16848	16006	317	1294443	1609492
3	1192686	1330828	1317520	33537	110907	115686	108745	2758	10130	18161	17616	390	1313723	1464675
4	1094488	1373867	1360128	39980	210251	216136	203168	2876	13719	16740	15736	360	1318458	1606743
5	1295645	1438954	1395785	43888	137522	156223	153099	3347	13380	18329	17413	348	1446547	1613506
6	1271710	1464798	1450150	42772	121822	152053	145971	4273	13963	14291	13719	218	1407495	1631142
7	1201590	1227574	1153920	38178	138861	155440	146114	4461	13825	14212	13928	200	1354276	1397226
8	1160665	1421983	1393543	39531	130838	143628	135010	2757	13184	18161	17253	341	1304687	1583772
9	1174982	1428343	1399776	36423	143289	222598	211468	4943	16620	17915	17378	279	1334891	1668856
10	1092150	1358479	1344894	35049	93969	139492	131122	2766	11273	13908	13630	253	1197392	1511879
11	1223652	1238225	1163932	39499	150026	214423	207990	4377	13724	13816	13678	189	1387402	1466464
12	1134181	1211273	1187048	34764	157352	166913	161906	4607	12469	18296	17564	370	1304002	1396482
13	1138374	1545864	1453112	46067	103359	150806	149298	4298	13644	13674	13127	208	1255377	1710344
14	1117957	1521374	1475733	48380	185975	203640	199567	4914	10383	18340	17973	326	1314315	1743354
15	1289317	1498006	1453066	41944	114032	164143	160860	4678	10144	18198	17834	348	1413493	1680347
16	1126216	1453426	1438892	43603	101619	134329	127613	2910	13712	18045	17504	334	1241547	1605800
17	1024810	1535007	1473607	40831	169890	215362	213208	3551	14647	17186	16670	296	1209347	1767555
18	1304453	1360632	1347026	38701	120256	152448	144826	4695	13437	18429	18060	341	1438146	1531509
19	1067035	1520348	1474738	38769	98227	112436	105690	2805	10425	16678	15677	312	1175687	1649462
20	1225138	1352598	1271442	35844	147007	158087	150183	4822	13545	15466	15002	288	1385690	1526151

Table 3 Performance evaluative of five echelon SC yielded by two variants of

DS	Performance evaluative based on On best of COD		Relative % increase		Performance evaluative based on On mean of COD		Relative % increase	
	LDIW	GLBIW	LDIW	GLBIW	LDIW	GLBIW	LDIW	GLBIW
1	1543119	1154448	33.67	0	1775216	1567425	13.26	0
2	1539271	1294443	18.91	0	1724027	1572145	9.66	0
3	1725410	1313723	31.34	0	1766869	1443881	22.37	0
4	1637152	1318458	24.17	0	1739283	1579032	10.15	0
5	1586971	1446547	9.71	0	1588428	1566296	1.41	0
6	1686685	1407495	19.84	0	1730968	1609840	7.52	0
7	1555374	1354276	14.85	0	1646565	1313961	25.31	0
8	1479264	1304687	13.38	0	1639068	1545807	6.03	0
9	1625544	1334891	21.77	0	1799105	1628622	10.47	0
10	1584726	1197392	32.35	0	1940007	1489647	30.23	0
11	1626355	1387402	17.22	0	1873215	1385600	35.19	0
12	1468381	1304002	12.61	0	1730689	1366517	26.65	0
13	1589946	1255377	26.65	0	1934271	1615537	19.73	0
14	1431311	1314315	8.90	0	1740678	1693273	2.80	0
15	1581209	1413493	11.87	0	1957436	1631760	19.96	0
16	1578233	1241547	27.12	0	1848175	1584008	16.68	0
17	1598472	1209347	32.18	0	1628048	1703486	0	4.63
18	1611795	1438146	12.07	0	1897609	1509912	25.68	0
19	1604356	1175687	36.46	0	1746680	1596105	9.43	0
20	1502535	1385690	8.43	0	1656404	1436627	15.30	0

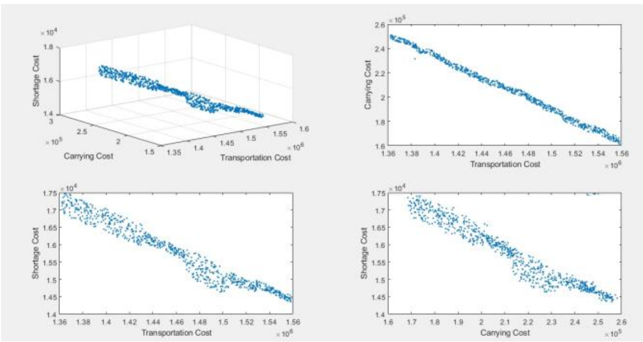

Fig. 1 Visualization of Pareto front of SC Model

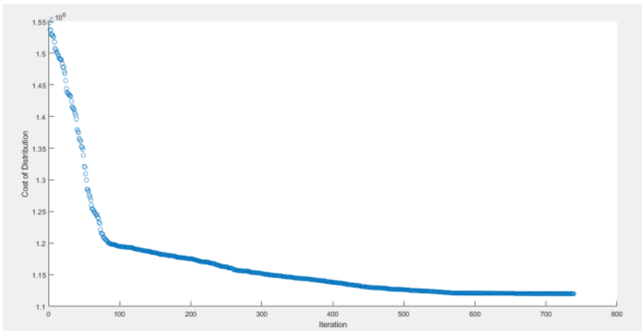

Fig. 2 Visualization of convergence of fitness function

respective best, worst, mean and standard deviation of TC, CC and ShC are recorded in table 1 and 2. Performance evaluation of the solutions obtained using LDIW and GLBIW are recorded in table 3. It is observed that GLBIW variant of PSO algorithm produced more optimal result for individual best solution and also for the mean of ten iterations. Inertia weight computed using GLBIW PSO variant orients each particle of the swarm towards the global best positions it has had till the previous iterations.

If the SC model is scalarized, all the conflicting individual objectives are represented as a single objective yielding only a single point in the pareto optimal front. The pareto optimal front of a replication of a demand scenario is depicted in Fig.1, which offers a set of non-dominated solutions of the SC model. The extreme low points in the solution space are called the utopia points. These utopia points represent the optimal minimum value of TC, CC and ShC. A pareto-optimal front helps to visualize the optimal trade-off between objectives to a problem and helps concentrate a particular region in the solution space. Fig. 2 depicts the visualization of COD in each iteration and it could be observed the cost moves drastically at faster pace in the initial iterations and slowly converges to optimal value.

VI. CONCLUSIONS

A five echelon SC model was developed to handle three objectives that minimize TC, CC and ShC. LDIW and GLBIW variants of PSO algorithm is used to compute the inertia weight that optimize the SC problem. Twenty demand scenarios were developed and optimized using LDIW and the same set of demand scenarios were handled by GLBIW variant of PSO algorithm. Each demand scenario is replicated ten times and the best of TC, CC and ShC were recorded along with the mean and standard deviation. A non-dominating pareto optimal front for an iteration of a demand scenario is presented to visualize the trade-off among possible solutions. GBLIW PSO variant produced the optimal results as the inertia weight influenced to include the solutions that are closer to globally best.

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