Impact of Social Welfare Methods on Multi-objective Resource Allocation in Energy Systems

Aisha Umair[1][a], Anders Clausen [1][b], Yves Demazeau [2][c] and Bo Nørregaard Jørgensen[1][d]

[1]*Center for Energy Informatics, University of Southern Denmark, Campusvej 55, Odense, Denmark*

[2]*Laboratoire d'Informatique de Grenoble, Batiment IMAG, 700 avenue Centrale, Grenoble, France*

Keywords: Evolutionary Computation, Multi-objective Optimization, Social Welfare, Energy Systems.

Abstract: Multi-agent resource allocation refers to the distribution of resources among agents. Resource allocation can be particularly challenging if the agents have conflicting objectives over multiple interdependent issues. In such cases, multi-objective optimization methods can be used to find an optimal allocation of resources, that maximizes social welfare. Social welfare refers to the welfare of the entire society of agents and therefore considered as a suitable metric for assessing the overall system performance in multi-agent resource allocation. In this paper we study and discuss different notions of social welfare and investigate their impact on the optimization outcome specifically for the problems comprising multiple conflicting objectives with interdependent issues. To this end, we implement and apply different notions of social welfare to a real-world, complex problem, where a resource domain is responsible for making allocation of energy resources to multiple energy intensive consumers (Commercial Greenhouse Growers). The problem is modeled as a multi-objective optimization context. Our results show how different social welfare methods affect the optimization outcome and result in different socially optimal resource allocations, depending on the behavior we expect from the system.

1 INTRODUCTION

Resource Allocation in a system involving multiple agents is an important research issue, that has gained a lot of attention in recent years. The agents may have conflicting and incommensurable objectives with rational behavior. Such scenarios may demand multi-objective optimization techniques based on the notion of Pareto optimality, to find an optimal allocation. In such cases, the optimization process ends up with multiple Pareto-optimal allocations which represent trade-offs between conflicting objectives. This in turn requires a selection of single outcome out of the resulting Pareto-optimal set at the termination of optimization process. In this regard, the concept of social welfare as explained in Welfare Economics and Social Choice Theory (Chevaleyre et al., 2006) is used to rank all the Pareto-optimal outcomes (allocations) depending on the behavior, desired from the system.

Several attempts have been made, which incorporate the notion of social welfare either within the search process or to select the final outcome in multi-objective optimization problems. The authors in (Li et al., 2009) proposed a mediated negotiation procedure to obtain fair agreements by using fair compromise direction while exploring the negotiation space. A non-linear negotiation protocol is proposed in (Fujita et al., 2012) to find a secure and fair outcome in a Pareto-optimal set. Similarly, the authors in (Finkelstein et al., 2009) proposed a multi-objective optimization approach to balance the requirements fulfillment between customers of Motorola Company for hand held communication devices, such that each customer is treated on fair basis. An extensible component-based multi-objective evolutionary approach has been proposed by authors in (Sørensen and Jørgensen, 2017), which considers a climate control problem to optimize and finally applies utilitarian social welfare to select one solution among Pareto-optimal solutions. The authors in (Darmann and Schauer, 2015) tries to maximize social welfare in terms of Nash product while distributing indivisible goods among agents.

To the best of our knowledge, the existing body of literature considers derivable and quasi-concave util-

[a] https://orcid.org/0000-0002-6949-9159
[b] https://orcid.org/0000-0003-1333-7705
[c] https://orcid.org/0000-0003-4059-9284
[d] https://orcid.org/0000-0001-5678-6602

Umair, A., Clausen, A., Demazeau, Y. and Jørgensen, B.
Impact of Social Welfare Methods on Multi-objective Resource Allocation in Energy Systems.
DOI: 10.5220/0007761101790186
In *Proceedings of the 8th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2019)*, pages 179-186
ISBN: 978-989-758-373-5

ity functions while applying social welfare criterion within the search process. This indicates that the approach cannot be applied to nonlinear utility functions scenarios. Work to investigate, compare and apply different notions of social welfare to a multi-objective problem for the selection of final outcome is also limited in existing literature. Further, the notion of social welfare is based on unnormalized costs in most studies. The consequence is that objectives may contribute unevenly towards the selection of a final outcome. In such a context, social welfare methods cannot be utilized to assess the overall performance in the application domains, as utility cannot be directly compared across objectives.

The main contributions of this paper are to 1) compare and evaluate different notions of social welfare on a common problem, 2) modify collective cost functions (CCFs) of social welfare methods by utilizing normalized costs for the selection of final outcome, 3) address the weaknesses of weighting mechanism by introducing the notion of relative importance graph, 4) evaluate modified social welfare methods on a real-world problem to compare their properties with respect to the selected optimization outcomes.

The paper is divided in six sections. Section 2 describes the methodology used to address multi-objective multi-issue (MOMI) problems and a detailed description of social welfare methods. The experimental setup is presented in section 3. Section 4 describes experiments and results. Section 5 presents some findings deduced from the results, and finally our conclusions are drawn in section 6.

2 METHODOLOGY

To perform resource allocation in MOMI problem, Controleum, a generic MOMI negotiation framework (Sørensen and Jørgensen, 2017), (Clausen et al., 2014) is used. Controleum solves an optimization problem with multiple objectives to generate a Pareto front over the problem that is described in section 3.

2.1 Multi-objective Optimization

The problem defines a MOMI optimization context consisting of **N** concerns, which negotiate over a set of **M** issues, $(s_1, s_2 \dots s_M)$. The issue represents a decision point over a resource, the value of which is negotiated by one- or several concerns. Each concern c_n, $n \in N$, defines a preference as a cost function, for each issue s_j, $j \in M$, over which the c_n wishes to negotiate. The optimization context has a Mediator, which is responsible for managing the optimization process (Umair, 2018). The Mediator searches for a contract, defined as a vector of M issues values $\boldsymbol{C} = s_1, \dots, s_M$, that satisfies the preferences of the concerns. The optimization process has three main phases, i.e., initiation phase, optimization phase and termination phase.

In the initiation phase, the Mediator initiates the optimization by generating a population of random contracts. Then the control goes to optimization phase, where the Mediator presents the contracts to each concern for evaluation. In response, each of the concerns assigns cost values to all the contracts in the population. The cost of the concern c_n for a contract C defined as $q_{(c_n,C)}$, describes the degree to which the proposed contract adheres to the preferences of the concern. Then, the Mediator selects the subset of non dominated contracts using *Pareto criterion*. After population selection, the Mediator generates the next population of contracts by performing mutation and crossover on randomly selected contracts from the Pareto set. This process is repeated until a termination criterion is met.

At termination, the optimization process will end up with multiple contracts on the Pareto front if the concerns have conflicting preferences. The Mediator is therefore responsible for selecting a final contract from the Pareto front adhering to the social welfare criterion selected for the problem.

2.1.1 Relative Importance of Concerns

The concerns may have different significance relative to each other. For example, achieving production goal in a greenhouse domain seems to be relatively more important than minimizing energy consumption. In this kind of situation, it is necessary to ensure the satisfaction of relatively more important objectives before the satisfaction of relatively less important objectives, to guarantee correct behavior of the system. The concerns may also end up in a conflict due to conflicting preferences. To handle such scenarios, an approach based on weighting factor is defined in (Liu et al., 2014), to specify the relative importance of users' preferences. This approach poses several weaknesses, 1) weights are problem dependent and must be carefully set by the user because the results are very much sensitive to weights ratio, 2) weights don't map well to the problem domain. To address the weaknesses of weights, we introduce the notion of relative importance of concerns to determine their order in the selection mechanism. The relative importance between concerns c_1 and c_2 is defined in terms of three integer values -1, 1 and 0. -1 means c_1 is relatively more important than c_2, 1 means c_1 is relatively less important than c_2 and 0 means c_1 is equally important to c_2. Once the relative importance of each concern towards every other concern is defined, the relative importance graph (RIG) is constructed, which is a directed graph defined as, $RIG = < N, E >$, where $N = \{N_1, N_2, \ldots, N_n\}$ is a set of nodes, and $E = \{E_1, E_2, \ldots, E_m\}$ is a set of edges. To construct a graph, a root node is created first and the first concern c_1 in the sorted list of concerns (which are sorted based on their relative importance) is added to the top most node, i.e., root. Then another concern c_2 is added by comparing it to the already added concern c_1. If the relative importance of c_1 and c_2 towards each other is equal, then the concern c_2 is placed in the same node N_i, which already contains concern c_1. Otherwise, a new node N_j is created and concern c_2 is placed in node N_j. Here, concern c_1 is placed above concern c_2. Finally, an edge is created from node N_i, containing c_1 to node N_j, containing c_2. The RIG is used in the selection mechanism, to select the final contract at termination of optimization process.

2.1.2 Selection of Final Contract

The selection of a final contract is carried out hierarchically using RIG along with one of the SWOs described in section 2.2. The SWO is applied first to the top level node in RIG. The selection mechanism will select a subset of contracts from the current population, which conforms to the preferences of the concerns in the top level node according to the applied SWO. A situation may arise where the subset from the top level selection contains a single contract. In that case, the next level nodes won't be traversed. Otherwise, the selection mechanism uses the subset in the next level node to further filter the contracts. This process continues until the subset contains only a single contract or all nodes are traversed. In the end, if there are multiple contracts in the subset of contracts, then one contract is randomly selected from the subset as a final contract, as all the remaining contracts have equal value to the concerns in the context.

2.2 Social Welfare Orderings

The concept of social welfare studied in Welfare Economics and Social Choice Theory is used to model the aggregation of concerns' individual preferences. Several means of quantifying the social welfare metric among concerns exist, which are used in the existing resource allocation applications to find an optimal allocation (Chevaleyre et al., 2006).

Every contract C, $C \in P_f$ generates a cost vector, as a result of concerns' evaluation of the contract. The concerns may have different nature of cost functions with different cost distributions. Therefore, 0-1 scaling is used to normalize concerns' costs by extracting minimum and maximum values from the non-dominated population of contracts for each concern (Umair, 2018). Suppose $q'_C = \{q'_{t_1,C}, q'_{t_2,C} \cdots, q'_{t_n,C}\} \in R^n$, is a normalized cost vector, where $q'_{t_i,C}$ is the normalized cost of i^{th} concern for contract C. The Collective Cost Function (CCF) represents a mapping from such vectors to the reals $f : R^n \rightarrow \mathbb{R}$. The different notions of social welfare can be modeled as a CCF. Each CCF gives rise to a corresponding Social Welfare Orderings (SWO), which defines a transitive and complete binary preference relation $\preceq$ on cost vectors. The SWOs are based on normalized costs. That is to ensure that all concerns contribute equally in the selection of final contract. The SWOs can be roughly classified in three categories, i.e, inequality, equality and overall utility based SWOs.

2.2.1 Inequality based SWO

This category comprises elitist social welfare method, which does not favour fairness among concerns.

Elitist Social Welfare. This SWO disregards fairness and equality among concerns. The elitist SWO ranks contracts based on the normalized cost of the best-off concern, as defined in equation 1.

$$SW_{EL}(C) = \min\{q'_{t_i,C} \mid t_i \in concerns\} \quad (1)$$

A contract C is preferred over contract C' $(C \prec C')$ if and only if (iff) $\overset{\uparrow}{q'}_{t_1,C} < \overset{\uparrow}{q'}_{t_1,C'}$, where $\overset{\uparrow}{q'}_C$ represents the reordering of the normalized cost vector $q'_C = \{q'_{t_1,C}, q'_{t_2,C}, \ldots, q'_{t_n,C}\}$ in an increasing order and therefore defined as, $\overset{\uparrow}{q'}_C = \{\overset{\uparrow}{q'}_{t_1,C}, \overset{\uparrow}{q'}_{t_2,C}, \ldots, \overset{\uparrow}{q'}_{t_n,C}\}$.

2.2.2 Equality based SWO

This category comprises six social welfare methods, i.e., egalitarian, lexi-min, approximated fairness, fairness analysis, quantitative fairness and entropy, which are based on the notion of fairness.

Egalitarian Social Welfare. This SWO offers a level of fairness and equality among concerns and defined as normalized cost of worst-off concern, shown in equation 2.

$$SW_E(C) = \max\{q'_{t_i,C} \mid t_i \in concerns\} \quad (2)$$

Hence $(C \prec C')$ iff $\overset{\downarrow}{q'}_{t_1,C} < \overset{\downarrow}{q'}_{t_1,C'}$, where $\overset{\downarrow}{q'}_C$ represents the reordering of the normalized cost vector

$q'_C = \{q'_{t_1,C}, q'_{t_2,C}, \ldots, q'_{t_n,C}\}$ in decreasing order and defined as, $\overset{\downarrow}{q'}_C = \{\overset{\downarrow}{q'}_{t_1,C}, \overset{\downarrow}{q'}_{t_2,C}, \ldots, \overset{\downarrow}{q'}_{t_n,C}\}$. This SWO has a weakness that it only takes into account normalized cost of worst-off concern while defining the ordering of contracts.

Lexi-min Ordering. This SWO is considered as a refinement of egalitarian SWO. In this SWO, $(C \prec C')$ iff there exists an integer $r \in \{1, \ldots, n\}$, such that $(\overset{\downarrow}{q'}_C)_i = (\overset{\downarrow}{q'}_{C'})_i$ for all $i < r$; and $(\overset{\downarrow}{q'}_C)_r < (\overset{\downarrow}{q'}_{C'})_r$ where $\overset{\downarrow}{q'}_C = \{\overset{\downarrow}{q'}_{t_1,C}, \overset{\downarrow}{q'}_{t_2,C}, \ldots, \overset{\downarrow}{q'}_{t_n,C}\}$ represents the reordering of the normalized cost vector $q'_C = \{q'_{t_1,C}, q'_{t_2,C}, \ldots, q'_{t_n,C}\}$ in a decreasing order.

The idea of lexi-min SWO is appealing in a sense that it overcomes the weakness with respect to egalitarian SWO. It starts by comparing the costs of worst-off concerns and if the costs of worst-off concerns coincide then it compares the costs of next worst-off concerns and so on.

Approximated Fairness. This SWO (Fujita et al., 2012) ranks contracts based on the squared sum of the deviation of individual normalized costs of the concerns from average of all concerns' costs as defined in equation 3.

$$SW_{AF}(C) = \sum_{i=1}^{n} \frac{(q'_{t_i,C} - q'_{avg,C})^2}{n} \tag{3}$$

where $q'_{avg,C} = \frac{\sum_{i=1}^{n}(q'_{t_i,C})}{n}$. Hence $(C \prec C')$ iff $SW_{AF}(C) < SW_{AF}(C')$. A contract C is considered ideal if its $SW_{AF}(C) = 0$.

Fairness Analysis. The concept of fairness analysis SWO (Finkelstein et al., 2009) ranks contracts based on the standard deviation of the normalized cost of each concern as defined in equation 4.

$$SW_{FA}(C) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(q'_{t_i,C} - q'_{avg,C})^2} \tag{4}$$

where $q'_{avg,C} = \frac{\sum_{i=1}^{n}(q'_{t_i,C})}{n}$. Hence $(C \prec C')$ iff $SW_{FA}(C) < SW_{FA}(C')$.

Quantitative Fairness. This SWO is based on Jain's index (Huaizhou et al., 2014), which is defined as the fairness measure based on resource allocation X, where n is the number of individuals. x_i is the amount of resource allocated to individuals $i = 1, 2, \ldots, n$ as shown in equation 5.

$$f(X) = \frac{[\sum_{i=1}^{n} x_i]^2}{n\sum_{i=1}^{n}(x_i)^2}, \quad 0 \le f(X) \le 1 \tag{5}$$

Fairness can be measured both in terms of resource allocation and utility. Contrary to allocation fairness, the fairness can be measured in terms of normalized cost of concerns. In this case, the Jain's index is equal to 0 when all concerns have the same cost. The quantitative fairness SWO with respect to concerns' normalized cost vectors is modified and redefined in equation 6.

$$SW_{QF}(C) = 1 - \frac{[\sum_{i=1}^{n}((q'_{t_i,C} + r)]^2}{n\sum_{i=1}^{n}((q'_{t_i,C} + r)^2} \tag{6}$$

where, $[r \in Z^+]$, $0 \le SW_{QF}(C) \le 1$. To avoid division by zero, a positive integer r is added to the normalized cost of each concern (equation 6). Hence $(C \prec C')$ iff $SW_{QF}(C) < SW_{QF}(C')$.

Entropy. This SWO (Shannon, 2001) is defined as the fairness measure based on resource allocation X, where n is the number of individuals and p_i is the proportion of resource X allocated to individual i. The entropy of the distribution X, i.e., uncertainty of the distribution X, is usually measured by H(X) as shown in equation 7.

$$H(X) = -\sum_{i=1}^{n}(p_i log_2 p_i) \tag{7}$$

where $p_i = \frac{x_i}{\sum_{i=1}^{n}(x_i)}$ and $log_2 p_i = \frac{ln(p_i)}{ln(2.0)}$. Assuming that the costs returned by concerns in response to the proportion of resource allocation, is a measure of fairness. The entropy SWO with respect to concerns' normalized cost vectors is modified and redefined in equation 8.

$$SW_{EN}(C) = \sigma - |\sum_{i=1}^{n}(p_i log_2 p_i)| \tag{8}$$

where $p_i = \frac{q'_{t_i,C} + r}{\sum_{i=1}^{n}(q'_{t_i,C} + r)}$ $[r \in Z^+]$. A positive integer r is added to the normalized cost of each concern to avoid division by zero (equation 8). Here σ is some arbitrarily large number $\gg 1$. The entropy SWO is smaller when contract is fair or vice versa. Hence $(C \prec C')$ iff $SW_{EN}(C) < SW_{EN}(C')$.

2.2.3 Overall Utility based SWO

This category comprises three social welfare methods, i.e., utilitarian, Nash product and median rank, which take into account overall utility of concerns.

Utilitarian Social Welfare. This SWO ranks contracts based on the sum of individual normalized costs of concerns as defined in equation 9.

$$SW_U(C) = \sum_{i=1}^{n} q'_{t_i,C} \tag{9}$$

Hence $(C \prec C')$ iff $\sum_{i=1}^{n} q'_{t_i,C} < \sum_{i=1}^{n} q'_{t_i,C'}$.

Nash Product This SWO combines the features of both utilitarian and egalitarian SWO to rank contracts based on the product of individual normalized costs of the concerns as defined in equation 10.

$$SW_N(C) = \prod_{i=1}^{n} q'_{t_i,C} \tag{10}$$

Hence $(C \prec C')$ iff $\prod_{i=1}^{n} q'_{t_i,C} < \prod_{i=1}^{n} q'_{t_i,C'}$. This notion of social welfare favors both overall well-being of concerns as well as reduced inequality among concerns. The overall well-being is achieved by the fact that, computing the product of concerns' costs, ensures that the total normalized cost of concerns will not increase too much as it will give rise to an increase in the product of the costs. On the other hand, reduced inequality is achieved by the fact that the contract with equal low costs for all concerns is always the one with lowest product of costs.

This SWO is applicable to non-negative and non-zero cost vectors otherwise the result of Nash product will fluctuate between negative and positive values and a single zero cost in the normalized cost vector will make rest of the costs meaningless. Therefore equation 10 is modified by adding a small positive value to the cost of each concern as shown in equation 11. This is how; ranking of contracts based on Nash CCF would still be meaningful for the cases where concerns return zero cost.

$$SW_N(C) = \prod_{i=1}^{n} (q'_{t_i,C} + r) \quad [r \in Z^{+}] \tag{11}$$

Median Rank Dictators. This SWO defines a social welfare based on the cost of middle-most concern as defined in equation 12. Let $(\overset{\downarrow}{q'}_C)_r$ represents the r_{th} largest normalized cost of any of the concerns over contract C, and $r = n/2$, in case n is even and $r = (n+1)/2$, in case n is odd. Hence $(C \prec C')$ iff $(\overset{\downarrow}{q'}_C)_r < (\overset{\downarrow}{q'}_{C'})_r$.

$$SW_{MR}(C) = (\overset{\downarrow}{q'}_C)_r \tag{12}$$

3 EXPERIMENTAL SETUP

The experimental setup is based on a specific resource allocation problem scenario, where a resource domain (RD) is responsible for making energy allocations to Commercial Greenhouse Growers (CGGs). CGGs of today are advanced production facilities, which require artificial supplementary lighting for plants growth especially in winter seasons (Umair, 2018).

To better illustrate the impact of SWOs on an optimization outcome, we have chosen to focus on the RD, which defines a MOMI context. In general, the approach allows for inter-domain negotiations to balance interdependent issues distributed across several problem domains. There are 7 concerns in RD in total. These concerns include one domain specific concern (DC), and two representative concerns (RCs), consumer RC (CRC) and consumer RC-sum (CRC-sum) for each CGG. The RCs represent the preferences of CGGs in the RD. The RCs in the RD negotiate over issues reflecting energy allocation plans, one for each CGG. An energy plan issue is a vector, $e_n = \{e_{1,n}, e_{2,n}, \ldots e_{t,n}\}$, describing an hourly allocation of energy to the CGGs for an entire day. The value of a time slot in the energy allocation plan issue e_n is 0 or 1 MWh. The configuration of concerns in RD is described in table 1. The RD uses the RIG, in order to select the final contract, where the DC in the RD is assigned high relative importance compared to the CRC and the CRC-sum to ensure an agreement state between concerns in case of their conflicting preferences. This configuration is chosen to resolve the conflict through graceful degradation of the production requirements in CGGs without disrupting local system operation. The number of CRCs in the RD depends on the number of CGGs connected to RD. There are three CGGs which are connected to RD, so one set of CRC and CRC-sum is used for each CGG.

4 EXPERIMENTS

Considering the problem scenario described in section 3, two sets of experiments have been conducted to study the impact of different notions of social welfare (described in section 2.2) on an optimization outcome in terms of resource allocation. Each set of experiments is run 20 times to show resilience towards the potential random behavior sparked by the use of genetic algorithm (GA).

The first set of experiments simulates a scenario with unconstrained resources. This means, sufficient amount of resources is available in the RD. In this set of experiments, all the CGGs have the same pro-

Table 1: Configuration of concerns in RD.

Concern	*Preference*	*Issue*	*Cost Function*	*Purpose*
DC	p_n, represents an hourly resource capacity i.e., upper bound on amount of resources that can be allocated	e_1, e_2, e_3	$q_n = \sum_{i=1}^{t} \lvert y_i - p_i \rvert$ where, $y = \sum_{n}^{N} e_n$	To change planned aggregated consumption of CGGs to ensure that combined allocation complies with resource capacity
CRC_n	d_n, represents the energy efficient demand profile for CGG_n	e_n	$q_n = \sum_{i=1}^{t} \lvert e_{i,n} - d_{i,n} \rvert$	To ensure that demand in each hour matches with allocated amount of energy
$CRC_{sum(n)}$	d_n represents the energy efficient demand profile for CGG_n	e_n	$q_n = \lvert \sum_{i=1}^{t} e_{i,n} - \sum_{i=1}^{t} d_{i,n} \rvert$	To ensure that correct amount of electricity is allocated for CGG_n it represents regardless of the time it is allocated

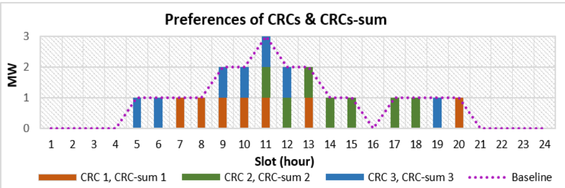


Figure 1: Preferences of CRCs and CRCs-sum.

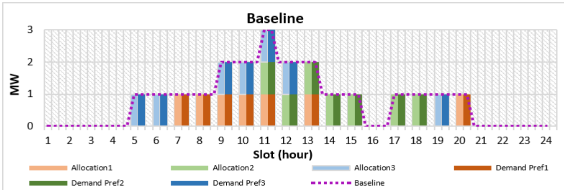


Figure 2: Results of baseline experiment.

duction goals, i.e., each of the CRCs and CRCs-sum is given the same demand preference in terms of amount. However the time slots in which resources are demanded, varies for each CRC and CRC-sum as shown in figure 1. The experiment is repeated multiple times, i.e., the experiment is run once for each notion of social welfare. These experiments serve to show how different notions of social welfare lead to the same optimization outcome, i.e., all the CRCs and CRCs-sum will be allocated their requested demand, in the scenarios where resources are unconstrained.

The second set of experiments simulates a scenario where the resources are constrained. This means, insufficient amount of resources is available in the RD. Likewise first set of experiments, the demand preferences for CRCs and CRCs-sum are equal (figure 1) and the experiment is repeated for each notion of social welfare. These experiments serve to show how different notions of social welfare lead to the different optimization outcomes in the scenarios where resources are constrained, i.e.,when allocating resources to CGGs in a resource-constrained setting, 1) overall utility based social welfare methods will lead to an optimization outcome, that favors overall well-being of CGGs, 2) inequality based social welfare method will lead to an optimization outcome, that disregards fairness and equality among CGGs, 3) fairness based notions of social welfare will lead to an optimization outcome, that favors fairness and equality among CGGs.

4.1 Baseline Experiment Results

Figure 2 shows the results of this experiment. A baseline profile represents the optimal demand profiles for the CGGs. The baseline profile received from each CGG will be regarded as a preference for their respective CRCs and CRCs-sum in the RD. The CRC and CRC-sum for each CGG in the RD play their role and influence the optimization process by negotiating over the issues, they are interested in. The CRCs and CRCs-sum in the RD will try to minimize the distance between their preference and the issue values, they negotiate over. This is how, in case of unconstrained resources, each CGG is provided with its preferred energy plan i.e. no change is forced upon the CGGs and therefore allocation matches with the demand in each time slot and corresponds to the baseline profile.

Table 2 shows the result of MOMI optimization process in terms of allocations and demands. A_1, A_2, and A_3 depict the electricity allocations (MWh) made by RD for CGG_1, CGG_2, and CGG_3 respectively at the termination of optimization process. Similarly D_1, D_2, and D_3 show the electricity demands (MWh) made by CGG_1, CGG_2, and CGG_3 respectively. As can been seen in table 2, allocation matches with the demand and each CGG is able to meet its demand preference.

4.2 Constrained Experiment Results

Figure 3 shows the preference of DC in the RD, which reflects the constrained resource scenario. The conflict can be seen at slot 11, 12 and 13, where a DC

Table 2: Results of MOMI Optimization.

Experiments	A_1	A_2	A_3	D_1	D_2	D_3
Baseline	7	7	7	7	7	7
Constrained (Inequality Based SWO)	6	7	5	7	7	7
Constrained (Equality Based SWOs)	6	6	6	7	7	7
Constrained (Overall Utility Based SWOs)	7	4	7	7	7	7

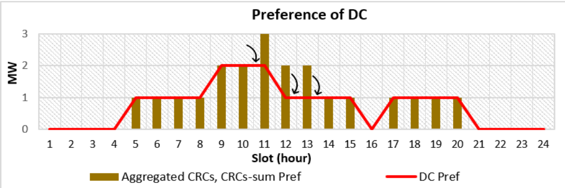
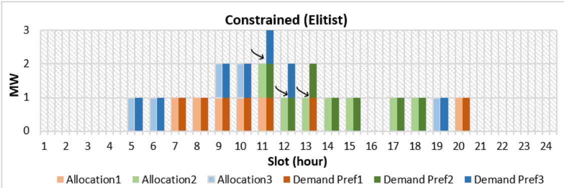
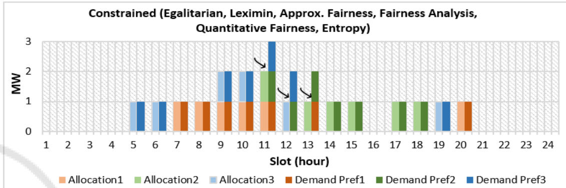


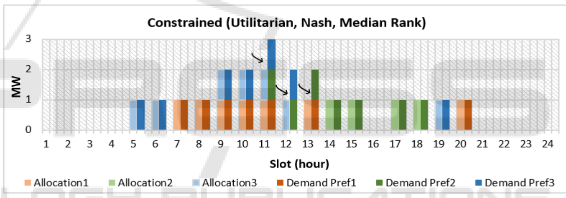
Figure 3: Preference of DC.



(a) Inequality based SWOs.



(b) Equality based SWOs.



(c) Overall utility based SWOs.

Figure 4: Results of constrained experiment.

requires modification to the baseline profile, by providing 1 MW less energy in each of the conflicting slots. This situation requires CGGs to shed their load in the above mentioned slots. The results can be seen in figures 4a to 4c.

Figure 4a shows the result of experiment with inequality based SWO. Here, the RIG based on elitist SWO is used for the selection of final contract in RD. As explained earlier in section 2.2, elitist SWO tries to minimize the cost of the best-off concern and ensures that at least one of the CGGs must achieve its goal. As anticipated, allocations are made in a way, where one of the CGGs, i.e., CGG_2 is provided with its most preferred energy profile, whereas the remaining two CGGs are forced to reduce their demands. Table 2 shows that CGG_1 and CGG_3 have made a compromise of 1 and 2 MW respectively, whereas CGG_2 meets its demand preference.

The same experiment is then repeated with SWOs, which favor fairness among CGGs. The experiment has been run once with each of the equality based SWOs. In each experiment, one of these SWOs is used for the selection of final contract. The results are shown in figure 4b. As can be seen that each of these fairness based SWOs in the RD, ensures that all the CGGs are treated equally and they will therefore all concede as necessary to bridge the gap of the conflict caused by the constrained resources. Here, CGG_3 sheds its load in slot 11, CGG_2 sheds its load in slot 12, whereas CGG_1 sheds its load in slot 13. Table 2 shows that all CGGs have made a compromise of 1 MW each and therefore deviated from their desired demand preferences.

Next, the experiment is repeated with SWOs, which favor the overall well-being of CGGs. The experiment was conducted using overall utility based SWOs, which all yielded similar results. The results are shown in figure 4c. As expected, each of these SWOs favors overall well-being of the group of CGGs. This explains that why the consequences of constrained resources are unevenly divided among CGGs, i.e., CGG_2 sheds its load in all the required slots 11, 12 and 13, whereas CGG_1 and CGG_3 are provided with the amount, they demanded. Similarly, table 2 shows that CGG_2 has made a compromise of 3 MW and deviated from its demand preference.

5 DISCUSSION

Taking into consideration the production requirements and different types of plants in the greenhouse domain, it is important to make a right choice about which notion of social welfare should be applied to select the optimization outcome. This may have a significant impact on plants with respect to their growth. For instance, in unconstrained resource settings, the results in figure 2 revealed that the selection of optimization outcome can be done using any notion of social welfare, as all the social welfare methods select the same outcome where all the CGGs are able to meet their demand requirements without making any compromise over production.

In constrained resource settings, we deduce some facts about the selection of social welfare method with respect to plant growth in CGGs. First, the inequality based SWO can be applied to select the final outcome specifically for long-day photoperiodic plants which are sensitive to the duration of day-night like rudbeckia and california poppy. That is to ensure at least one of the CGGs gets the required amount of light, instead of making all the CGGs affected by the constrained resources, as seen in figure 4a. Second, overall utility based SWOs can be used to select the allocation for day-neutral plants which do not require any specific day length like rose and tomato growing. This is because all these methods take into account overall well-being of CGGs (see figure 4c). The CGG, which takes the consequences of constrained resources will not be affected too much due to their day-neutral sensitivity. Third, for short-day plants like chrysanthemum, christmas cactus, and poinsettia, it is recommended to use equality based SWOs (figure 4b). This is because they do not require long lighting hours. In case of insufficient resources, CGGs can easily make a fair compromise with respect to their demand preference without affecting plant growth (Kumpf, 2019).

6 CONCLUSION

This paper discusses the properties and impact of different notions of social welfare on an optimization outcome in MOMI optimization problems. In this regard, a GA based MOMI optimization approach is used to describe a complex, real world problem. To study the impact of social welfare methods, two sets of experiments are conducted in unconstrained and constrained resource settings respectively. The results show that different notions of social welfare lead to different optimization outcomes and selection of the social welfare method depends on the behavior we expect from the system.

In future works, we intend to investigate the impact of social welfare methods on different real-world problems which exhibit additional complexity in terms of number of objectives. We aim to focus on 1) combining different notions of social welfare to select the final optimization outcome, i.e., in cases where multiple contracts yield same utilitarian score, equality based SWOs can be applied to select the most fair contract out of the resulting set of contracts yielding high utilitarian score, 2) applying different notion of social welfare at each level of RIG, i.e., in cases where each level of RIG comprises more than one concern.

REFERENCES

Chevaleyre, Y., Dunne, P. E., Endriss, U., Lang, J., Lemaitre, M., Maudet, N., Padget, J., Phelps, S., Rodriguez-Aguilar, J. A., and Sousa, P. (2006). Issues in multiagent resource allocation. *Informatica*, 30(1).

Clausen, A., Demazeau, Y., and Jørgensen, B. N. (2014). An agent-based framework for aggregation of manageable distributed energy resources. In *International Conference on PAAMS*, pages 214–225. Springer.

Darmann, A. and Schauer, J. (2015). Maximizing nash product social welfare in allocating indivisible goods. *European Journal of Operational Research*, 247(2):548–559.

Finkelstein, A., Harman, M., Mansouri, S. A., Ren, J., and Zhang, Y. (2009). A search based approach to fairness analysis in requirement assignments to aid negotiation, mediation and decision making. *Requirements Engineering*, 14(4):231–245.

Fujita, K., Ito, T., and Klein, M. (2012). A secure and fair protocol that addresses weaknesses of the nash bargaining solution in nonlinear negotiation. *Group Decision and Negotiation*, 21(1):29–47.

Huaizhou, S., Prasad, R. V., Onur, E., and Niemegeers, I. (2014). Fairness in wireless networks: Issues, measures and challenges. *IEEE Communications Surveys & Tutorials*, 16(1):5–24.

Kumpf, J. (2019). Lighting systems. [Online; accessed on 4-January-2019].

Li, M., Vo, Q. B., and Kowalczyk, R. (2009). Searching for fair joint gains in agent-based negotiation. In *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 2*, pages 1049–1056.

Liu, Y., Yuen, C., Huang, S., Hassan, N. U., Wang, X., and Xie, S. (2014). Peak-to-average ratio constrained demand-side management with consumer's preference in residential smart grid. *IEEE Journal of Selected Topics in Signal Processing*, 8(6):1084–1097.

Shannon, C. E. (2001). A mathematical theory of communication. *ACM SIGMOBILE*, 5(1):3–55.

Sørensen, J. C. and Jørgensen, B. N. (2017). An extensible component-based multi-objective evolutionary algorithm framework. In *Proceedings of the 6th ICSCA*, pages 191–197. ACM.

Umair, A. (2018). *An Agent Based Approach to Coordination of Resource Allocation and Process Performance*. PhD thesis, Syddansk Universitet. Det Tekniske Fakultet.