This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2019.2954673, IEEE Transactions on Sustainable Energy

Sizing Battery Energy Storage Systems: Using Multi-Objective Optimisation to Overcome the Investment Scale Problem of Annual Worth

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***Abstract*— The financial objective, when sizing a Battery Energy Storage System (BESS) for installation in a microgrid, is to maximise the difference between discounted BESS benefits and discounted BESS costs. This may be described as maximising Annual Worth (AW). However, one drawback of sizing microgrid BESS using AW is that the scale of investment is not taken into consideration. This can lead to unrealistic BESS sizes. This paper presents two multi-objective optimisation (MOO) models to account for the scale of investment required in sizing BESS. The first model, Paired Comparison, utilises two objective functions: Daily Worth (DW), which maximises daily benefit cost differences a BESS installation provides a microgrid; and Daily Cost (DC), which minimises the daily cost of a BESS installation. The second model, called Rating Method, uses the objective functions DW and Daily Benefit-Cost Ratio (DBCR), the latter of which maximises the relative measure of BESS benefit and BESS cost. Both models are solved for a test microgrid system under three different scenarios using Compromise Programming (CP). For system designers who rank objective functions by importance, the Rating Method is the appropriate approach, whereas system designers who rank objective functions by absolute values should use Paired Comparison.**

***Index Terms*— Multi-Objective Optimisation, Battery Energy Storage Systems, Net Present Value, Benefit-Cost Ratio, Annual Worth, Equivalent Annual Cost, Compromise Programming, Normal Boundary Intersection Method**

I. Introduction

Each year more and more renewable generation is connected to electrical grids around the world. The European Union alone has seen a net increase of 158.3GW of installed wind and 107.3GW of installed solar PV from 2000-2017 [1]. The added value of renewable generation is that it reduces CO_2 per MWh of energy produced when compared with traditional thermal generation. However, this added benefit comes with the disadvantage of intermittency, which can lead to scheduling, frequency and voltage difficulties for the grid. To overcome this intermittency, Battery Energy Storage Systems (BESS) are one possible solution. For a BESS to be connected to a grid (microgrid, distribution grid, etc.) it must be sized appropriately. Sizing of BESS entails determining the optimum power rating (e.g. MW) and/or energy capacity rating (e.g. MWh). “Optimum” in this case means, that for all feasible BESS sizes available for a given grid connection, only one power rating and/or one energy capacity rating represents the best-case scenario.

This work was supported by Science Foundation Ireland and DP Energy Ireland Ltd. under grant no. 12/RC/2302

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BESS can have financial objectives or technical objectives as in [2], or a hybrid of the two [3]. Outlining BESS objectives before sizing allows optimisation models to maximise or minimise power and/or energy ratings, which results in the optimum BESS size. This paper is solely concerned with the treatment of financial objectives. The most common financial objective in BESS sizing is reducing the operational cost of a either a microgrid [4-7] or distribution grid [8, 9]. Here the addition of BESS to a grid allows the transfer of energy over time, with charging and discharging periods optimised to reduce the overall grid operation cost. The reduction in grid operation cost can be interpreted as an added benefit of installing a BESS within the grid. Optimum BESS size is established when the benefit value is furthest from the BESS cost. Other financial objectives include installing a BESS to maximise the profit of a renewable energy installation, with a wind farm example given by [10]. While this approach is different to [4-9], the same concept applies, that is, maximising difference between added benefits and costs of BESS. The discounted cash flows methods used by [4-9] are known as Equivalent Annual Cost (EAC) or Annual Worth (AW) [11]. A positive AW value indicates that benefits are greater than costs. AW is analogous to Net Present Value (NPV) [12], with AW widely used in the engineering community and the accounting community preferring NPV. For simplicity, this paper uses the term AW when referring to the absolute difference between annual discounted benefits and costs.

Selecting an investment project size by maximising the difference between discounted benefits and costs has significant disadvantages. The issue that AW demonstrates is one of scale. AW is an absolute measure and therefore does not take into account the effort required to achieve the objective. Table I illustrates the scale problem of AW, modified from [13]. Project S is given as the best option with an AW twice that of project T. However, the capital expenditure of Project S is 2000 times that of Project T. As access to capital is limited in real-world cases, clearly Project T is the preferred option. As highlighted by [13], for AW to be an appropriate metric for comparing and ranking mutually exclusive projects, the budget must be fixed and each project must have the same investment, which is impracticable for BESS sizing. Importantly, this investment scale problem is applicable to BESS sizing methodologies that employ a direct search approach, such as those in [10, 14]. This approach uses

TABLE I
Illustration of AW Criterion Masking Scale of Effort Required

Project	Annual Benefit ($)	Annual Cost ($)	AW ($)	AW as % of cost
S	2,002,000	2,000,000	2000	0.1
T	2000	1000	1000	100

an algorithmic strategy that does not evaluate incremental BESS sizes but rather directly searches for the optimum solution. Maximisation of the objective function is carried out using optimisation software packages which directly search for values of the decision variables that give the maximum value of the objective function. This direct search approach results in a single optimal BESS size that satisfies the maximum AW. All other BESS sizes are deemed suboptimal, however there could exist BESS sizes unconsidered which retain a significant portion of AW but with much less cost. Since only a single optimal BESS size is outputted using direct approaches, this results in BESS sizing by direct search suffering the same investment scale issue as those outlined in Table 1.

To overcome the scale problem, other financial objectives must be considered, while still attempting to maximise AW. These financial objectives must address the core issue, i.e. consideration of the scale of investment required. One approach is to make investment an objective function itself. Maximising AW while minimising investment are conflicting objectives as increasing AW will require a larger BESS with higher cost. The other approach is to utilise relative rather than absolute measures as an objective function. One such measure is Benefit-Cost Ratio (BCR). Maximising BCR and maximising AW are conflicting as BCR is a relative measure of the same variables used by AW. It is possible to have both AW and BCR increasing over certain BESS size ranges, but ultimately as maximum AW is being reached, the rate of change of AW will decrease and therefore BCR will also decrease. The investment scale problem is inescapable in any setting which maximises AW, regardless of consideration of technical objectives or location. Therefore, since technical objectives or location do not negate the issue of investment scale they are omitted from this paper for clarity purposes.

The aim of this paper is to investigate if sizing a BESS via multiple financial objectives is an effective technique for overcoming the scale problem of AW. The multi-objective combinations considered are 1) AW and BESS Cost, and 2) AW and BCR. Objectively, this is achieved by developing a microgrid optimisation model where the addition of BESS is sought. The multi-objective combinations 1) and 2) are optimised for sizing BESS being added to a microgrid. To determine the effectiveness of each approach, different scenarios are analysed, and results compared.

II. Literature Review

While optimising a sole objective function has been extensively studied for sizing BESS [4-10], optimising multiple conflicting objectives has been given less attention. One approach taken by [15] optimised simultaneously three financial objective functions, 1) maximise operating profit of a BESS installation in a distribution grid, 2) minimise BESS energy capital cost and 3) minimise BESS power capital cost. This approach did not size a BESS but rather the authors determined which BESS capital cost combination would give a positive AW and by extension what AW can be expected for a given capital cost combination. A constant BESS was chosen, and capital costs varied. As part of future work the authors suggest that other financial indicators should be considered such as Internal Rate of Return (IRR) and Return of Capital Employed (ROCE). Both these indicators offer different investment performance evaluation than AW which makes them of interest for this paper. Calculating IRR is finding the discount rate which gives a value of zero AW. IRR can be interpreted as a rate of investment measure. Maximising IRR can give conflicting investment decisions compared with maximising AW when different project initial investment levels are compared [16, 17]. IRR has been used by [18] to evaluate the financial performance of BESS. However, IRR can be a complex calculation for direct search optimisation procedures by either trial and error approach or extracting the discount rate which is raised to different power values for every time period. ROCE is a relative measure and is very similar calculation to BCR. BCR has been used by [19] for energy storage planning in distribution networks. The authors maximised the AW of energy storage but did not co-optimise two other objectives – Discounted Payback Period (DPP) and BCR. Rather, DPP and BCR were evaluated at maximum AW. This approach does not allow for co-optimisation and therefore the energy storage size is selected post optimisation. Others have used BCR to evaluate the performance of optimal power flow model for sizing and allocating BESS in a microgrid [20].

Optimising multiple objective functions has also been applied to objectives other than financial indicators. The authors in [21] used multi-objective Mixed Integer Linear Programming (MILP) to minimise CO_2 emissions and minimise operating cost for a community energy storage system. A single BESS size is considered for multiple battery technologies and the levelized cost of electricity and payback period are evaluated. Another study which sized a BESS for a PV-based microgrid maximised both the annual net profit and PV consumptive rate [22]. The problem was solved using non-dominated sorting genetic algorithm II (NSGA-II). Interestingly, [15, 22] did not make any reference to weighting of their respective objective functions, whereas [21] indicates that each objective function is equally weighted. This implies that the authors were more interested in a set of solutions rather than a single output from their models.

Other works closely related to this study use Bilevel Optimisation (BO) with two financial objective functions. BO captures hierarchical processes, where optimisation of a lower level objective function acts as a constraint in an upper level objective function. If a hierarchical process exists in a problem, then BO is considered a suitable method [23]. BO was used by [24] to size and site a BESS within a transmission grid. Here the authors considered two financial objectives. The upper level objective seeks to minimise the grid operation cost and BESS cost with profit constraints, while the lower level objective seeks to minimise grid operating cost. Similar to [24], the authors in [25] also used BO for different perspectives within the grid. Their model seeks to solve an upper level objective by maximising the profit of merchant Energy Storage (ES), while at the same time minimising grid operating cost in the lower level objective. While BO is a suitable method for hierarchical processes, and a suitable technique for capturing different perspectives within the electrical grid, the problem being considered in this paper is a perspective-neutral approach, and therefore does not lend itself to using BO. The financial objectives as part of this paper are competing objectives and not hierarchical. Furthermore, both [24] and [25] used profit and investment constraints for BESS installation. These constraints can provide some success in avoiding the pitfalls of maximum

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AW, as highlighted in the previous section. Placing these constraints into a BESS sizing optimisation model allows minimum rates of return to be enforced. However, these constraints have significant disadvantages which are discussed from this point onwards. Placing a rate of return within the profit constraint allows the ES owner to apply a relative measure to BESS investments, similarly a maximum investment constraint can have the same outcome. Although this method can be effective, using the same rate of return value while varying model input parameters may lessen its effectiveness for overcoming the AW scale problem. Having knowledge about the final solution beforehand may allow rate of return adjustment, however this knowledge may not be readily available. Another point to note is that rate of return values greater than one are difficult to interpret. It is given that investment projects with rate of return greater than or equal to one are accepted and those values of less than one are rejected [26]. However, deciding on a particular rate of return value from those that are greater than one may be difficult, as theoretically all investment projects are deemed acceptable. While the authors of both [24] and [25] used profit and investment constraints, these were not discussed in the context of overcoming the pitfalls of maximising AW.

III. Problem Formulation

Multi-objective optimisation (MOO) allows for tradeoff analysis of two or more objective functions. The problem structure is outlined by (1) and (2) and is formulated as two separate MOO problems capturing two different approaches.

$$F_1(x) = [f_{AW}(x),\ f_{Cost}(x)]^T \tag{1}$$

$$F_2(x) = [f_{AW}(x),\ f_{BCR}(x)]^T \tag{2}$$

where $f_{AW}(x)$ is the AW objective function (28), $f_{Cost}(x)$ is the cost objective function (29) and $f_{BCR}(x)$ is the BCR objective function (30). There is a significant difference between $F_1(x)$ and $F_2(x)$. This difference is due to the individual ability of $f_{Cost}(x)$ or $f_{BCR}(x)$ to size BESS separately of $f_{AW}(x)$. For approach (2) both objective functions are capable of sizing BESS autonomously. Each contains both benefits and costs within its objective function. For approach (1) $f_{AW}(x)$ has this ability, whereas $f_{Cost}(x)$ only considers BESS cost and therefore is incapable of sizing a BESS independently. Rather, $f_{Cost}(x)$ is used as a measure of amount spent. This difference leads to different interpretations of the tradeoff within each approach. In approach (1) the question for tradeoff is, how much change is allowed in $f_{AW}(x)$ with respect to change in $f_{Cost}(x)$. In approach (2), the question for tradeoff is deciding which objective function is more important.

This difference between $F_1(x)$ and $F_2(x)$ requires different solution techniques for MOO methods involving weighted objective functions. Weights are assigned to each objective function for *a priori* articulation of preferences in certain MOO methods [27]. The authors of [28] identify two broad classes of approach, Paired Comparison and Rating Method. In Paired Comparison the objective functions remain in their original state so that tradeoff analysis between absolute values of each objective function is permitted. This approach lends itself to $F_1(x)$ where the change in AW with respect to change in cost is sought. In the Rating Method approach the objective functions are normalised. This provides a unitless comparison of the objective functions while also reducing any magnitude dominance of either objective function. This allows objective functions to be ranked in terms of importance where system designers select a ranking out of 10 for each objective function [29]. The Rating Method described is equivalent to the problem described by $F_2(x)$. Given that $F_1(x)$ is Paired Comparison and $F_2(x)$ is Rating Method, the appropriate techniques are applied to each. Fig. 1 gives an overview of the problem formulation.

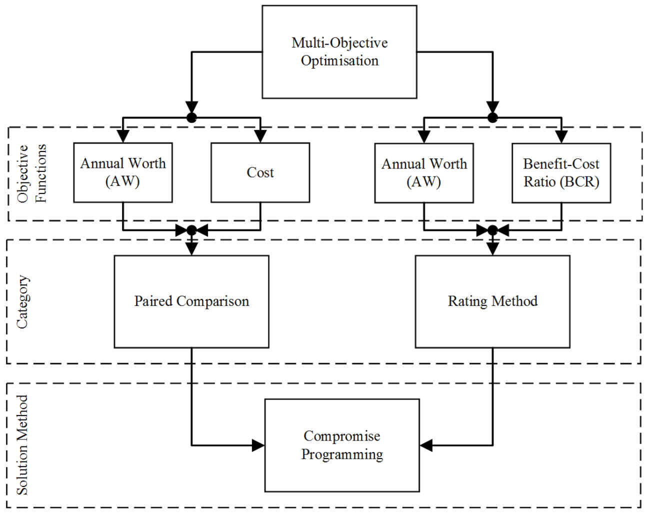

Fig. 1. Structure of MOO problem formulation used in this paper.

IV. System Modeling

A microgrid without a BESS is used as the reference case. The reference microgrid consists of two microturbines, wind turbine, solar PV, connection to large external grid and load. The owner of the BESS is the owner of the microgrid, who also owns the generation and demand. The first microturbine is must run while the second has a minimum generation limit with startup cost. No microgrid reserve requirement and no power losses is assumed. The addition of a BESS is sought to improve the financial performance of the microgrid i.e. to operate the microgrid at lower cost.

A. Model

1) BESS Model

The BESS energy capacity rating is given by (3), where S_i is a set of parameters signifying BESS size and XB_i is a set of binary decision variables.

$$E_{BESS} = \sum_{i=1}^{b} S_i XB_i \quad \forall i, \tag{3}$$

There are two reasons for implementing E_{BESS} as a summation of binary variables. The first is that BESS are manufactured based on incremental sizes rather than a continuous range of sizes. The second reason allows for the linearisation of the BCR objective function, which is described in more detail in Part B of this section. S is given by (4)

$$S_{i+1} = 2 \times S_i \quad \forall i, \tag{4}$$

The initial value of S_i is the size increment available for BESS. The value given to b needs to be large enough to capture all available BESS sizes but not so large as to increase computation time significantly.

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C-rate is a design constraint that limits the number of power and energy rating combinations for BESS and is given by (5) and (6)

$$XP_t^- \geq C_{rate}E_{BESS}\ \forall t \quad (5)$$

$$XP_t^+ \leq C_{rate}E_{BESS}\ \forall t \quad (6)$$

where t is time period, XP_t^- and XP_t^+ are the charging and discharging power variables respectively, located at the BESS and microgrid connection point and are bounded by (7) and (8).

$$-WP_t - SP_t \leq XP_t^- \leq 0, \forall t \quad (7)$$

$$0 \leq XP_t^+, \forall t \quad (8)$$

where WP_t and SP_t are the amount of power at time t interval from wind and solar respectively. This constraint enforces BESS charging from renewable energy. Allowing $XP_t^+$to have no upper bound, the C-rate constraint in (6) ensures that the BESS discharge power variable is within acceptable limits.

The equations to govern the amount of energy in the BESS during each time interval is given by (9) and (10).

$$\Delta t XP_t^- \eta_c + \Delta t XP_t^+/\eta_d + \sum_{i=1}^{t-1} \Delta t SP_i^- \eta_c + \Delta t SP_i^+/\eta_d \leq 0, \forall t \quad (9)$$

$$\Delta t XP_t^- \eta_c + \Delta t XP_t^+/\eta_d + \sum_{i=1}^{t-1} \Delta t SP_i^- \eta_c + \Delta t SP_i^+/\eta_d \geq -E_{BESS}, \forall t \quad (10)$$

where η_c and η_d are the charge and discharge efficiencies respectfully, Δt is the time interval, SP_i^- and SP_i^+ are BESS power variables and are given by (11) and (12).

$$XP_t^- = SP_i^-, t = i \quad (11)$$

$$XP_t^+ = SP_i^+, t = i \quad (12)$$

BESS manufacturers place limits on the allowable energy throughput over a period of time, such as a year. In exchange for these limits, customers receive a warranty for their BESS. It is assumed that the warranty period is sectionalized into yearly limits. This is a further BESS model constraint as is given by (13)

$$\sum_{t=1}^{T} \Delta t XP_t^+/\eta_d \leq \frac{E_{thru}}{365} \quad (13)$$

where T is the number of time intervals in one year, E_{thru} is the energy throughput allowed by the BESS manufacturer under warranty.

2) Microgrid Model

The variable L_t represents the microgrid load at time interval t. This load must equal generation at all times t and is specified by (14)

$$XM_{1,t} + (M_2^-)XM_{2,t}^b + XM_{2,t} + WP_t + SP_t + XP_t^- + XP_t^+ + XG_t^- + XG_t^+ = L_t\ \forall t \quad (14)$$

where $XM_{1,t}$ is the first microturbine (must run) with a minimum value as shown in (15), the second microturbine has the binary variable $XM_{2,t}^b$ for minimum generation at start-up (M_2^-) and $XM_{2,t}$ for dispatchable power, XG_t^- and XG_t^+ are power exported and imported from the external grid respectively. No curtailment of renewable energy is assumed so that all power from renewable sources must be accepted. The variables in (14) are bounded by (15), (16), (17) and (18).

$$M_1^- \leq XM_{1,t} \leq M_1^+\ \forall t \quad (15)$$

$$0 \leq XM_{2,t} \leq M_2^+ - M_2^-\ \forall t \quad (16)$$

$$-G^- \leq XG_t^- \leq 0\ \forall t \quad (17)$$

$$0 \leq XG_t^+ \leq G^+\ \forall t \quad (18)$$

Given that the second microturbine requires a minimum generation of M_2^-, a further constraint (19) is applied to the model. This ensures that if $XM_{2,t}$ is selected to run then the minimum generation requirement is imposed.

$$(M_2^+ - M_2^-)XM_{2,t}^b \geq XM_{2,t}\ \forall t \quad (19)$$

$$XU_t \geq XM_{2,t+1}^b - XM_{2,t}^b\ \forall t \quad (20)$$

The variable XU_t (20) is introduced to capture the start-up cost of the second microturbine.

3) Time Horizon

Typically, AW and BCR are maximised over one year if the same cash flows are assumed for each year. The purpose of this paper is to demonstrate the effectiveness of the methodology for a simple microgrid test case. Therefore, to save computation time, BESS sizing is done over one day, with 24-hour periods. The BESS benefit per day is given by the added benefit over 24 hours, whereas the coefficient for BESS cost per day is given by (21). This approach has been used by [4, 5].

$$E_{Cost} = \left(\left(\left(\frac{r(1+r)^l}{(1+r)^l - 1} \right) E_{CC} \right) + E_{MC} \right) \frac{1}{365} \quad (21)$$

where r is the financing interest rate, l is length of the project, E_{CC} ($/kWh) is the capital expense of the BESS along with auxiliary equipment and civil works, E_{MC} is the annual maintenance cost in $/kWh per year.

B. Objective Functions

The objective functions used for Paired Comparison are $f_{AW}(x)$ (28) consisting of benefits and cost, and $f_{Cost}(x)$ (29) with only cost. Rather than analysing the total benefit and cost of the microgrid for a given day, the added benefit of the BESS is considered. This requires optimisation of the microgrid without a BESS to find reference case for comparison. The operational cost of the microgrid without a BESS is given by (22).

$$C_{Grid}^{BESS^-} = \sum_t \big(XM_{1,t}C_{M1} + XM_{2,t}^{SU}C_{M1}^{SU} + (M_2^-)XM_{2,t}^b C_{M2} + XM_{2,t}C_{M2} \big) \quad (22)$$

where $C_{Grid}^{BESS^-}$ is the cost to run the microgrid with no BESS, $XM_{2,t}^{SU}$ is a binary variable for startup cost, C_{M1} is the dispatch cost of microturbine 1, C_{M1}^{SU} and C_{M2} are the startup and dispatch costs of microturbine 2 respectively. It is assumed that wind, solar, external grid and BESS have no dispatch

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costs. The total benefits of the microgrid without BESS are given by (23)

$$B_{Grid}^{BESS^-} = \Delta t \sum_t XM_{1,t}Q_t + (M_2^-)XM_{2,t}^bQ_t + XM_{2,t}Q_t + WP_tQ_t + SP_tQ_t + XG_t^+(-Q_t) \quad (23)$$

where Q_t is the price of electricity for time interval t. For XG_t^+ the price of electricity is negative as this is buying electricity from the external grid. The maximum difference between microgrid benefit and cost without a BESS is given by (24). This value remains constant and only requires solving once.

$$OC = max\left(B_{Grid}^{BESS^-} - C_{Grid}^{BESS^-}\right) \quad (24)$$

As the BESS considered here has no dispatch cost, then $C_{Grid}^{BESS^-} = C_{Grid}^{BESS^+}$, where $C_{Grid}^{BESS^+}$ is the cost of operating the microgrid when a BESS is installed. The benefit of BESS connected to a microgrid is given by (25).

$$B_{Grid}^{BESS^+} = \Delta t \sum_t XM_{1,t}Q_t + (M_2^-)XM_{2,t}^bQ_t + XM_{2,t}Q_t + WP_tQ_t + SP_tQ_t + XP_t^-Q_t + XP_t^+Q_t + XG_t^+(-Q_t) \quad (25)$$

Therefore, the added benefit of installing a BESS to a microgrid is shown in (26) and the cost of BESS is shown in (27).

$$B_{BESS} = \left(B_{Grid}^{BESS^+} - C_{Grid}^{BESS^+}\right) - OC \quad (26)$$

$$C_{BESS} = E_{Cost}E_{BESS} \quad (27)$$

Taking (26) and (27) as the benefit and cost respectively, the objective functions for Paired Comparison are formulated in (28) and (29). As this analysis is for one day, the AW term is restated as Daily Worth $f_{DW}(x)$ and the term $f_{Cost}(x)$ is changed to $f_{DC}(x)$

$$\frac{f_{AW}(x)}{365} = f_{DW}(x) = B_{BESS} - C_{BESS} \quad (28)$$

$$\frac{f_{Cost}(x)}{365} = f_{DC}(x) = C_{BESS} \quad (29)$$

$x = \{XM_{1,t}, XM_{2,t}^{SU}, XM_{2,t}^b, XM_{2,t}, XP_t^-, XP_t^+, XG_t^-, XG_t^+, XB_i\}$ for the decision variable.

For the Rating Method, objective functions $f_{DW}(x)$ and $f_{DBCR}(x)$ are optimised. The change of annual BCR to Daily Benefit Cost Ratio (DBCR) is shown as $f_{BCR}(x)$ to $f_{DBCR}(x)$, where $f_{DBCR}(x)$ is given by (30).

$$\frac{f_{BCR}(x)}{365} = f_{DBCR}(x) = \frac{B_{BESS}}{C_{BESS}} \quad (30)$$

$$f_{DBCR}(x) = \gamma \quad (31)$$

$$z_i \leq \gamma^+ XB_i \quad (32)$$

$$z_i \leq \gamma \quad (33)$$

$$z_i \geq \gamma - \gamma^+(1 - XB_i) \quad (34)$$

$$\sum_{i=1}^{a} XB_i \geq 1 \quad (35)$$

To ensure that the problem remains linear the constraints (31), (32), (33), (34) and (35) are applied to convert the nonlinear equation (30) to linear form, where γ^+ is some value larger than the maximum of γ, z_i is the variable assigned to the product of γ and XB.

C. Multi Objective – Paired Comparison, Rating Method and Compromise Programming

Compromise Programming (CP) is a MOO method which can find non-convex solutions within a Pareto set. Non-convex solutions are of importance to the sizing problems being considered as large benefit gains are expected from the reduction in startup cost of microgrid generators. The CP formulation, developed by [30, 31], is shown in (36) for Paired Comparison and in (37) for the Rating Method, whose form is applicable to the MOO problem in this paper.

$$min\left\{\left[w_1\left(f_{DW}^+ - \boldsymbol{P}_{a,1}\right)\right]^p + \left[w_2\left(f_{DC}^+ - \boldsymbol{P}_{a,2}\right)\right]^p\right\}^{\frac{1}{p}} \quad (36)$$

$$min\left\{\left[\lambda_1\left(\frac{f_{DW}^+ - \boldsymbol{P}_{a,1}}{f_{DW}^+ - f_{DW}^-}\right)\right]^p + \left[\lambda_2\left(\frac{f_{DBCR}^+ - \boldsymbol{P}_{a,2}}{f_{DBCR}^+ - f_{DBCR}^-}\right)\right]^p\right\}^{\frac{1}{p}} \quad (37)$$

where w is the corresponding weight for each objective function. The interpretation of the weights is given by $dF_{DC}/dF_{DW} = w_1/w_2$. $\lambda \in \mathbb{Z}^+$ and is the importance of each objective function, p is a metric parameter, f_{DW}^+, f_{DBCR}^+ and f_{DC}^+ are utopia points, f_{DW}^- and f_{DBCR}^- are nadir points. $\boldsymbol{P}$ is a matrix of Pareto solutions for DW and DBCR objective functions. $\boldsymbol{P}$ is evaluated using the solution algorithm in the next section. As a MOO method, CP attempts to find a set (or point) on the Pareto front that is closest to the infeasible utopia point. The Euclidean distance from the Pareto front to the utopia point is minimised. Typically, the utopia point is the maximum or minimum (depending on problem) of each objective function. When p is equal to one, this minimises the distance of minimum regret of not achieving the utopia point, and when equal to ∞, minimises the distance of maximum regret of not achieving the utopia point [30, 31]. Varying p from 1 to ∞ can also give a set of points on the Pareto front.

V. Solution Algorithm

The software used for this analysis was MATLAB 9.3 with the intlinprog function for optimisation. To utilise CP from the previous section, within MATLAB's functionality, the Pareto Front is evaluated beforehand. The Pareto front is developed by employing the Normal Boundary Intersection (NBI) method. NBI is a MOO method, and was developed by [32] to overcome disadvantages of the Weighted Sum Method, namely, generating points in non-convex regions and even spacing of Pareto points. The NBI formulation is shown in (38) and is applied to the MOO problem in this paper by (39), (40) and (41), where e is a column vector of ones, j is DW, k is DC when optimising Paired Comparison or DBCR when optimising the Rating Method.

$$\max_{x,D} s.t., \Phi\beta + D\hat{n} = F(x) \quad (38)$$

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$$\Phi\beta = \begin{bmatrix} \left(\dfrac{f_j(x) - f_j(x_j)}{f_j(x_k) - f_j(x_j)}\right) & \left(\dfrac{f_j(x) - f_j(x_j)}{f_j(x_k) - f_j(x_j)}\right) \\ \left(\dfrac{f_k(x) - f_k(x_k)}{f_k(x_j) - f_k(x_k)}\right) & \left(\dfrac{f_k(x) - f_k(x_k)}{f_k(x_j) - f_k(x_k)}\right) \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} \quad (39)$$

$$D\hat{n} = D(-\Phi e) \quad (40)$$

$$F(x) = \begin{bmatrix} \left(\dfrac{f_j(x) - f_j(x_j)}{f_j(x_k) - f_j(x_j)}\right) \\ \left(\dfrac{f_k(x) - f_k(x_k)}{f_k(x_j) - f_k(x_k)}\right) \end{bmatrix} \quad (41)$$

The matrix Φ is also called the pay-off matrix and when combined with β gives the Convex Hull of Individual Minima (CHIM). In two-dimensional space, CHIM can be thought of as a line connecting the maximum of two conflicting objective functions. The values in Φ are as follows: $f_j(x_j)$ which is the value of f_j when j is maximised, $f_j(x_k)$ which is the value of f_j when k is maximised, $f_k(x_j)$ which is the value of f_k when j is maximized and $f_k(x_k)$ which is the value of f_k when k is maximized. Also shown in Φ is the normalisation of the values. $\hat{n}$ is the unit normal to the CHIM. Therefore, by maximising D, the resulting expression $\Phi\beta + D\hat{n}$ gives access to all points along the normal and varying β allows for selecting different points along CHIM. The equality in (38) ensures that the maximum value of D is constrained by the boundary of the Pareto Front at $F(x)$, while maximising x gives the largest value for F. The outline for the solution algorithm is shown in Fig. 2. The change in β is determined by the number of points that are needed in the Pareto front. For every iteration of maximising D, the value of each objective function is recorded in matrix $\boldsymbol{P}$. Equation (36) and (37) is evaluated for every row of matrix $\boldsymbol{P}$, with the minimum value being the optimum point for CP. The algorithm was run on a Dell Latitude E5470 laptop with Intel Core i7-6600 CPU @2.60GHz and 16GB of RAM. For scenario 1, with the algorithm running 24 electricity trading periods of analysis, the time to completion is 22 seconds, for comparison with 96 trading periods taking 183 seconds. The number of variables to solve for in the 24 electricity periods is 273 with 993 variables to solve for in the 96 trading periods.

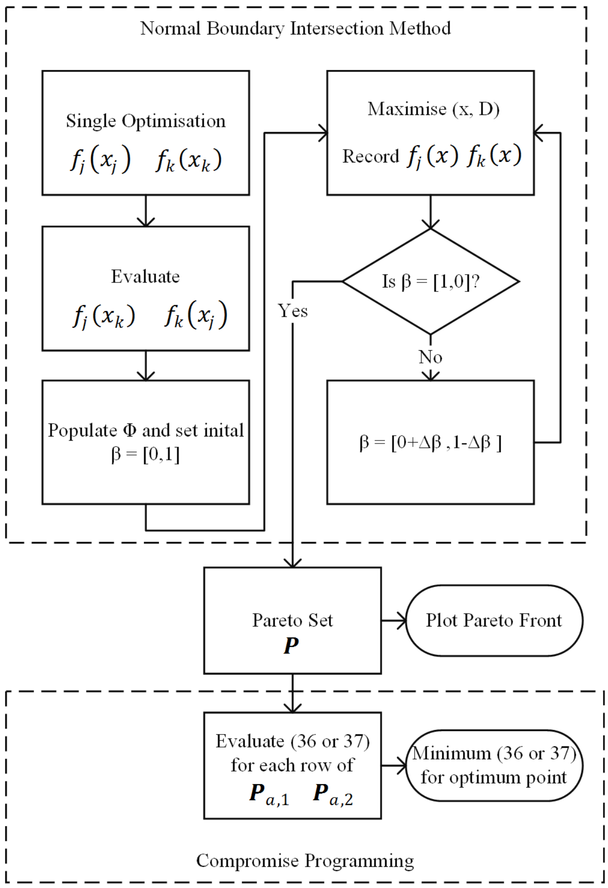

Fig. 2. Flow diagram of solution algorithm. The NBI method develops the Pareto Front first and CP uses the developed Pareto set to find the BESS solution

VI. Scenarios and Data

Three different illustrative scenarios of electricity market price are utilised, shown in Fig. 3, so that different Pareto Front shapes can be analysed This is a methodology paper where the focus is not to generate a specific system design but to show the workings of the proposed methodology. Therefore, the scenarios are for illustrative purposes. Electricity market price has a significant role in determining which generators are dispatched, which in turn influences Pareto Front shape. Scenario 1 is a 75% increase in electricity market price for each trading period from the scenario based on the widely used paper [4]. Scenarios 2 and 3 are a 50% and 25% decrease in electricity market price respectively for each trading period from the same scenario used in [4]. The price increase of scenario 1 promotes the dispatch of expensive generation whereas scenario 2 and 3 import more electricity from the external grid. Scenario 1 has capital costs (E_{CC}) of 593 $/kWh, operation and maintenance cost (E_{MC}) of 0.04 $/kWh per year and efficiency values η_c and η_d both 86% respectively. All values are taken from [33] based on Lithium BESS. Scenarios 2 and 3 have capital costs of 342 $/kWh.

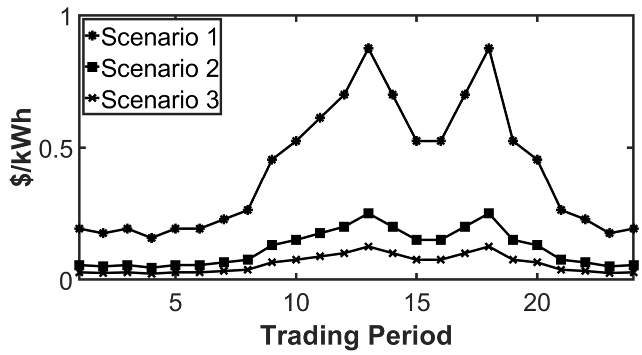

Fig. 3. Market Price scenarios utilised in this study. Variation of market prices over one day for three scenarios used in this study. Prices shown in decreasing order from scenario 1 with the highest price to scenario 3 with the lowest price.

TABLE II
MICROGRID DATA FOR COST AND GENERATION

Gen	($/kW) variable	($/start) variable	(Min P kW) variable	(Max P kW) variable
MT1	(0.13) C_{M1}	N/A	(1000) ${M_1}^-$	(2000) ${M_1}^+$
MT2	(0.35) C_{M2}	(30) C_{M1}^{SU}	(100) ${M_2}^-$	(1000) ${M_2}^+$
External Grid	N/A	N/A	(-1000) G^-	1000 G^+

The following assumptions are used for each scenario: C_{rate} is 0.5, b is 14, initial S_i is 1, Δt is 1, E_{thru} is 1kWh throughput per 1kWh of installed BESS capacity, Interest rate of finance r is 8%, project length is 10 years and γ^+ is 10. The load of the microgrid (L_t) is shown in Fig. 5 (b) and (c) along with wind $(WP_t -$ highlighted blue) and solar $(SP_t -$ highlighted orange) power profile respectively. Given that wind and solar must be dispatched, their values do not change for each scenario. The data in Table II is taken from [4] and is the same for each scenario.

VII. Analysis

The effectiveness of each approach, Paired Comparison and Rating Method, is assessed for their ability to size projects within the “knee” region of the Pareto Front. The knee region is a set of points on the Pareto Front where a small change in either objective function corresponds to a large change in another objective function. The significance of this is that reducing or increasing objective functions within the knee region has damaging effect on the optimum solution. Therefore, choosing a point within the knee region represents a better decision. This concept has been used to find knee regions at any location along a Pareto Front [34, 35]. However, the main concern for this paper is knee regions presented near maximum DW which allows focus of this analysis on weighting allocation of each objective function.

Taking Scenario 1 for each approach, Paired Comparison and Rating Method are shown in Fig. 4 (a) and (b) respectively. For Paired Comparison, objective functions DW and Cost are optimised. Point A in Fig. 4 (a) has a weighting w_1 of 2 and w_2 of 1, with a p value of 2 to realise any non-convex Pareto points. By applying these values, the system designer is inferring that they are willing to accept a DW change of \$1 for a change of \$2 in increased cost. Using these weightings, the BESS size at Point A is 1964 kWh. However, Point A is not in the knee region. Assigning weights in an absolute tradeoff situation, such as in Paired Comparison, only allows system designers to allocate preference to objective functions by the absolute difference between them. This approach does not allow system designers to find knee regions. Knee regions can form in any location on the Pareto Front under any circumstances. For example, if DW values where changed but the shape of the Pareto remained the same, then the weighting values w_1 of 2 and w_2 of 1 could give solutions within the knee region but only under these changed DW values. This highlights that two Pareto fronts with the same shape, but different absolute values, will give different optimal solutions for the knee region when the same weightings are used. Therefore, in Paired Comparison, knowledge about the final solution is required to ensure certainty of obtaining values within the knee region. One possible workaround is to normalise both DW and Cost objective functions, however as stated earlier, the cost objective function is incapable for sizing a BESS in isolation and therefore normalising would be meaningless. Point B in Fig. 4 (a) has a weighting w_1 of 8 and w_2 of 1. Point B is located in the knee region. However, as stated earlier, these weightings may not work for different Pareto sets. While the Paired Comparison approach is not suitable for sizing within knee regions, it does have merit. If the system designer understands the tradeoff they are seeking, meaning they are unconcerned with finding knee regions, then this method does allow for obtaining a meaningful solution.

Unlike the Paired Comparison approach which infers weightings as absolute tradeoff values, the Rating Method determines solutions by importance of each objective function. The Rating Method ask system designers to rank each objective out of 10. For BESS sizing this presents system designers with an easier question to answer than the tradeoff question for Paired Comparison. The Rating Method captures the importance of objective functions through normalising. This also allows the same weighting allocation across different Pareto Fronts, which is not suitable in Paired Comparison. Fig. 4 (b) outlines the optimum BESS size with weightings λ_1 and λ_2 as 10 and 2 respectively. This can be interrupted as DW with a rating of 10 out of 10 and DBCR with a rating of 2 out of 10. These weighting values reflect the interest in knees regions close to maximum DW. Selecting a higher value for λ_2 would move the focus closer to maximum DBCR. The p value is maintained at 2. What is clear from Fig. 4 (b) is that there is a predominat knee region. A significant point to note is the large BESS size difference between maximum DW and the optimised BESS size in Fig. 4 (b). The BESS size at maximum DW (\$342) is 3862 kWh whereas the Rating Method solution BESS size is 2343 kWh with a DW of \$331. The Rating Method solution BESS size has 97% of the total DW available but achieves this with a BESS size that is 60.7% of the maximum BESS size. Therefore, allowing a drop of 3% in (DW) profit will give a reduction of 39.3% in BESS size and capital spending. This solution represents a more realistic sizing approach and helps overcome the AW scaling problem.

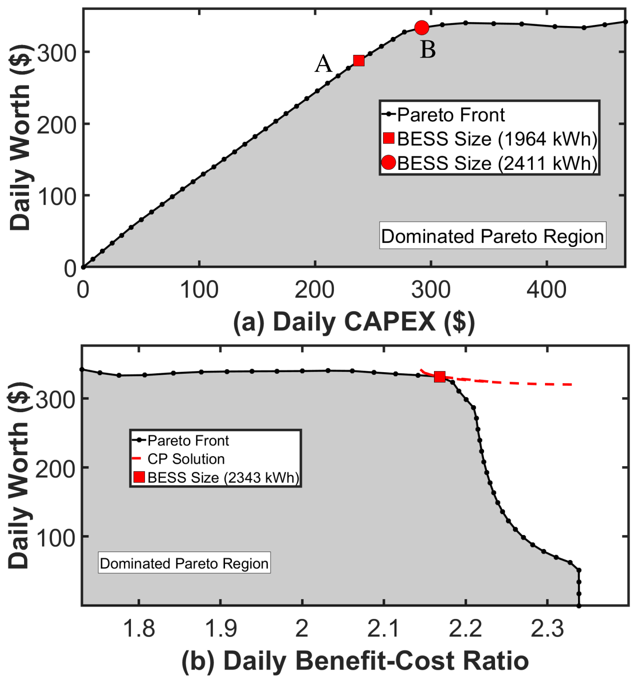

Fig. 4. (a) Paired Comparison of DW and Cost objective functions with tradeoff of two different weight values for scenario 1 and (b) Rating Method of DW and DBCR objective functions for scenario 1.

Pareto Front shape and the formation of knees is influenced be several factors. For scenario 2, the Pareto front, CP solution, attainable dominated points and microgrid dispatch profiles are shown in Fig. 5. Solution points to the left of the vertical dashed line in Fig. 5 (a) are attainable dominated points and are

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2019.2954673, IEEE Transactions on Sustainable Energy

therefore not part of Pareto front. The attainable dominated points undergo a significant change between DW \$40 and \$50, where both functions begin to increase. This change is caused by the shutdown of generator two when the BESS reached critical size. Fig. 5 (b) is the dispatch profile at point D where DW is \$47.90 and BESS size is 3379 kWh. Fig. 5 (c) is the dispatch profile at point C with DW equal to \$42.7 and BESS size of 3119 kWh. These two points represent a significant shift. The main difference occurs at trading period 17, with a smaller difference at trading period 14. Point D represents the next BESS size after point C where the DW value is greater

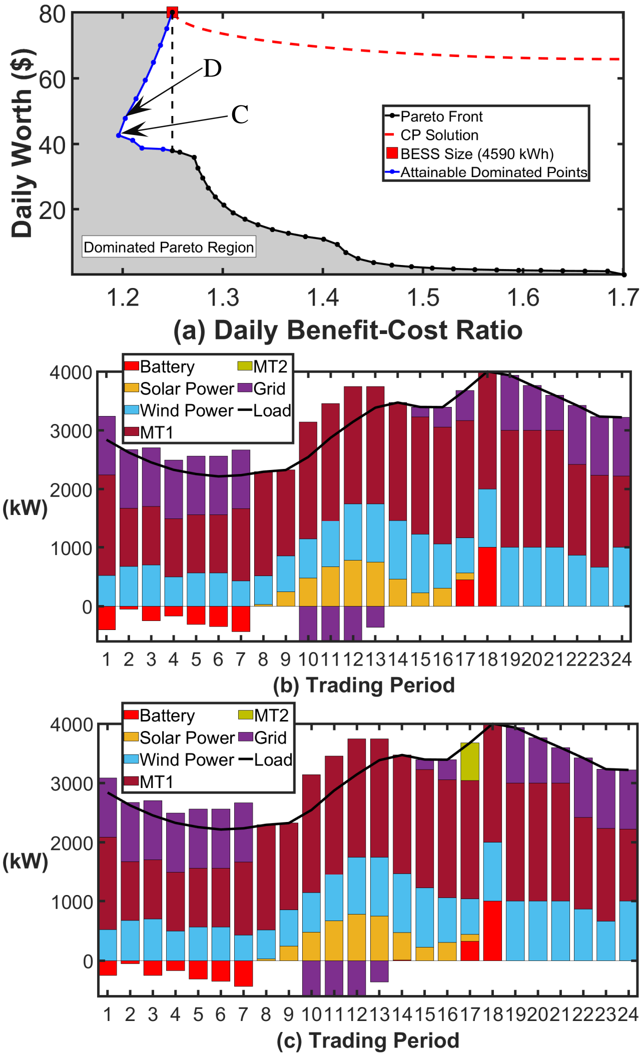

Fig. 5. (a) DW and DBCR showing effect of microgrid dispatch on Pareto Front (b) Dispatch Profile at point D with DW of \$47.9 and (c) Dispatch Profile at point C with DW of \$42.7. All for scenario 2.

than \$42.7. When the BESS reaches point D, the BESS is large enough to shut down microturbine 2 generator for trading period 17. This shutdown gives a large sudden increase in benefit value to the microgrid as the startup costs are replaced with cheaper electricity stored in a BESS. This reduced cost in the form of extra benefit causes a significant rise in DW value along with a rise in DBCR. This particular situation occurs when large sudden benefits are realised, and can have significant effect on the shape of the Pareto solution, and can have significant effect on the shape of the Pareto solution. Points C and D are attainable dominated points and cannot been recommended as potential BESS sizes for this application as better solutions exist on Pareto front.

The percentage differences shown for scenario 1 may not exist in every BESS sizing problem. The following example show this and why the methods used in this paper hold regardless. Fig. 6 illustrates the Pareto Front of DW and DBCR for scenario 3. The weighting values used for λ_1 and λ_2 are 10 and 2 respectively. Fig. 6 has no knee region within the vicinity of maximum DW, with only two slight knees in the middle and

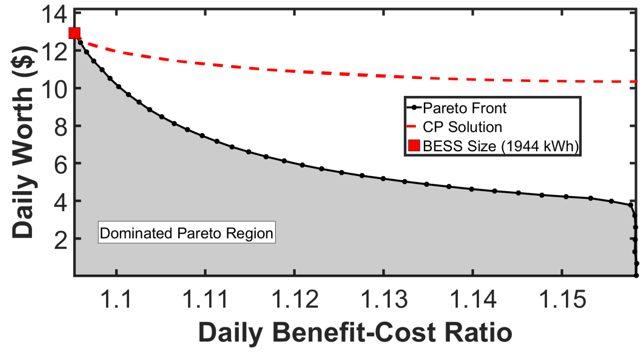

Fig. 6. DW and DBCR for scenario 3 showing insignificant knee regions

near maximum DBCR. The maximum BESS size 1944 kWh is selected for scenario 3. This point is selected as the change in DBCR objective function is relatively constant in the region of maximum DW. Therefore, DBCR has less influence on the final decision. This demonstrates the ability of the Rating method to also select maximum DW BESS sizes.

System designers need to know which values of w_1, w_2, λ_1 and λ_2 to use. As highlighted previously the main concern for sizing BESS is significant knee regions near maximum DW. These knee regions represent a large change in capital spend for a small gain in DW (depending on the severity of the knee region). It was shown that Paired Comparison is not effective for finding knee regions near maximum DW due to the inability of constant w_1 and w_2 values to produce consistent results for varying DW values but with similar Pareto Front shapes. Therefore, having a prescribed value for w_1 and w_2 is not possible. The only possibility for w_1 and w_2 is that the system designer knows the absolute trade-off they want beforehand, which may be the case. For the Rating Method, an acceptable value to use is 10 for λ_1 and 2 for λ_2 which gives the system designer the flexibility to size BESS up to maximum DW when no knee regions are present. Also, this provides protection for sizing BESS when knee regions are more pronounced near maximum DW.

VIII. Conclusion

The problem of scaling associated with sizing BESS by maximizing DW is addressed utilising the methods outlined in this paper. This paper presents a novel method for determining BESS size based on multi-objective optimisation of two financial objectives. Compromise Programming is utilised to apply weightings to objectives functions in both Paired Comparison and Rating Method. Three different price scenarios are modelled to show the effectiveness of each approach. Analysis of the methods show that:

1) CP is an effective MOO technique for finding the optimal BESS size to overcome the investment scale problem. The advantage of using CP is that it provides a single solution from a Pareto Front when the weightings are applied to represent objective function importance.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2019.2954673, IEEE Transactions on Sustainable Energy

Also, CP is able to provide solutions in non-convex regions which is likely in microgrid settings due to the change in DW that occurs from the minimum power start-up requirements of dispatchable generators.

2) Applying absolute tradeoff measures for determining knee regions is not an effective technique for finding optimum BESS sizes. Absolute value tradeoff is suitable for system designers who can clearly identify their absolute tradeoff values between objective functions and are not concerned with finding solutions in knee regions.
3) The Rating Method is more applicable for BESS sizing. For scenario 1, the Rating Method provided a drop in DW of 3% with a capital expenditure drop of 39.3%, which represents a more realistic BESS sizing decision. Further to this, not all knee regions will give such percentage differences. The Rating Method presents an easier question for system designers to answer and is more suitable for finding knee regions than Paired Comparison. Also, the Rating Method can find maximum DW with no knee region in the Pareto Set.
4) Finding solutions within the maximum DW regions requires a high weighting value for DW objective function and low value for DBCR objective function. The values used in this study, 10 for λ_1 and 2 for λ_2, represent acceptable weightings that can find optimal BESS sizes when the investment scale has and doesn't have a significant influence on the final BESS size.

It is acknowledged that other objectives rather than just purely financial objectives should be considered as part of any future work. For example, system operational requirements such as reserve provision or voltage/frequency regulation could be incorporated in the approach, or microgrid operational constraints associated with dispatch of the MT units and renewable generators.

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