A Multi-Objective Approach for Energy Management in a Microgrid Scenario

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***Abstract*—In this work, a preference-based, demand response (DR) multi-objective optimization model based on real-time electricity price is presented to solve the problem of optimal residential load management. The purpose of such a model is threefold: 1) to minimize the costs associated with consumption; 2) to minimize the inconvenience caused to consumers; and 3) to minimize the rebound peak occurrence. Potential solutions to the underlying multi-objective optimization problem are subject to a set of electrical and operational constraints related to home appliances categories and the utilization of distributed energy resources (DER) and energy storage systems (ESS). The use of the proposed model is illustrated in a realistic microgrid scenario where suitable solutions were found by the Non-Dominated Sorting Genetic Algorithm III (NSGA-III). These solutions determine new operational periods for home appliances as well as the utilization of DER and ESS for the planning horizon while considering consumer preferences. Besides helping consumers to take advantage of the benefits offered by DR, the experimental results show that the multi-objective DR model together with the NSGA-III algorithm can effectively minimize energy-consumption costs as well as reduce inconvenience costs and rebound peaks occurrences.**

***Index Terms*—demand response, microgrid, NSGA-III, optimization, smart grid**

I. Introduction

The increase of the global population has caused a greater complexity on the electricity supply. Therefore, studies and researches on the efficiency and reliability of electric power systems are necessary in order to avoid interruptions in the supply of electricity and the increase in prices, among other problems [1].

At the same time, the depletion of conventional energy sources worldwide and concern for the environment are also increasing rapidly [2]. One of the solutions to help overcome such problems is to incorporate an advanced measurement infrastructure, combined with information and communication technologies and smart meters through a smart grid (SG). An SG is a system that applies information and communication technologies (ICT) to improve the interaction between all the devices of an electrical power system (EPS) and consumers connected to it [3]. This interaction can be used by end consumers to improve their electricity consumption pattern in order to reduce the cost associated with electricity consumption.

The authors in [4] state that the demand response control methodologies and smart appliances can optimize the use of electrical resources more efficiently. In this sense, the authors in [5], [6] defined demand response (DR), in a SG context, as a program that provides various incentives and benefits to end consumers to change their electricity consumption patterns in response to changes in the electricity price over time or when electrical power network reliability is compromised by any EPS overhead. Such measures can be used to reduce the peak load demand instead of enlarging the generation capacity or reinforcing the EPS. The most common DR programs are based on price, in which a tariff model is used to help the user to adjust their electricity consumption patterns in response to electricity price deviation.

Based on the previous definition of DR, it could be a well-adopted concept on microgrids. A microgrid (MG) can be described as a cluster of distributed energy resources (DER), renewable energy resources (RRES), energy storage systems (ESS), and local loads, that can operate connected to the main grid or in islanding mode [7]. The MG allows for more efficient, reliable, and environmental friendly energy production, by increasing the deployment of distributed generation (DG), especially through RRES, as well as distributed ESS [8].

Although MG energy management has been studied with several different approaches in recent studies, as maximizing revenue of microgrid and minimizing environmental pollution [9], [10], improving dynamic performance by considering economic aspects [11], optimizing operation cost and economic performance [12], [13], and improving reliability of microgrid [14], as well as DR problems, such as [15], [16], [17], [18], [19], a preference-driven optimization mechanism and the scheduling of residential loads considering the different operating characteristics of the different categories of home appliances has not been well analyzed. Besides this, when this scheduling is contented focused only on cost and inconvenience minimization, it is possible that the electricity consumption concentrates in specific time intervals (the ones which has the lowest price and higher user convenience). If every home or MG is given the same price information, with a algorithm that utilizes opportunistically the times with low energy prices, energy consumption peak will happen at these times. This effect is called rebound peak and must be avoid to prevent outages and other problems in such times [20].

As the programming of the home appliances within the same time interval and the scheduling of RRES and the ESS requires time and specific knowledge on the part of the consumer [21], and the residential management scheduling must take into account consumer preferences regarding the use of these appliances and the price variation of electricity, in this paper, a preference-based multi-objective programming model is for energy management in a microgrid. The proposed model aims to optimize the consumption cost, consumer satisfaction and the rebound peak occurrence in a simultaneous way. A typical basic microgrid is studied, where the production side includes a photovoltaic panel (PV) system as a renewable energy resource and an ESS. *Constrained Non-Dominated Sorted Genetic Algorithm* (NSGA-III) [22] algorithm is applied to solve the proposed multi-objective problem. Several simulations, case studies and comparative studies are carried out to demonstrate the efficiency and viability of the proposed methodology.

II. Methodology

This section presents the multi-objective DR optimization model solved using the Constrained NSGA-III algorithm to manage the loads of all the appliances, taking into account the real-time pricing (RTP) [23] structure, the operational characteristics of each appliance, the renewable energy resources and the energy storage system. The common characteristics of power consumption and appliance-operating constraints for the objective functions f1, f2, and f3 are presented in [24]. Also are presented the basic concepts of Constrained NSGA-III, which is the technique used to solve the problem.

A. Problem Modelling

The multi-objective DR optimization model proposed in this work has three objective functions: $f1$, $f2$ and $f3$. The first one ($f1$) is related to the costs associated with the electricity consumption, the second one ($f2$), with the cost associated with the inconvenience caused to the end consumers in relation to the optimized planning of the use of home appliances provided by the multi-objective model. The last one ($f3$) is related to the occurrence of rebound peaks, which involves the difference between the peak demand and the average demand.

The function $f1$ used in the proposed multi-objective model, is formulated as follows:

$$\begin{gathered} Minimize \sum_{i=1}^{N} E_i \sum_{t=1}^{T} (Pr_t * DSA_{t,i})^2 \\ *(1 - (DSRRES_{t,i} - DSESS_{t,i})^2) \end{gathered} \tag{1}$$

where N is the number of home appliances; $E_i (i = 1, \ldots, N)$ represents the vector for the electrical energy consumption of home devices i when in operation; T is the time horizon; Pr_t is the price of electricity at time t. $DSA_{t,i}$ (Daily Setup of Appliances), $DSRRES_{t,i}$ (Daily Setup of Renewable Energy Resources), and $DSESS_{t,i}$ (Daily Setup of Energy Storage System) are binary matrix with the daily setup of operation of home appliances, renewable energy resources and energy storage system, respectively. $DSA_{t,i}$ refers to the load scheduling matrix with the following configuration:

$$DSA_{t,i} = \begin{cases} 1, & \text{if appliance } i \text{ is on at time } t, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

The $DSRRES_{t,i}$ refers to the planning matrix of RRES, and has the following configuration:

$$DSRRES_{t,i} = \begin{cases} 1, & \text{if appliance } i \text{ is consuming power from RRES at time } t, \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

The $DSRRES_{t,i}$ defines the scheduling of home appliances that consume power from RRES. In this work, RRES is composed by a system of photovoltaic panels (PVs) installed in the consumer's house. PV output power depends on cells temperature and solar irradiance at maximum power point (MPP) situation, expressed in (4) [25]. The temperature of the *m*-th cell of the PV is calculated by (4), and then the output power of PV at each time *t*, $t = 1, ..., T$ can be achieved by (5) [25]. Equation (6) corresponds to the inequality constraint for ensuring that the consumption of renewable energy by home appliances is lower than or equal to the output power of the photovoltaic system.

$$\begin{gathered} T_m(t) = T_{amp} + \frac{G_T(t)}{G_{T_{STC}}} * (NOCT - 20), \\ t = 1, ..., T \end{gathered} \tag{4}$$

$$\begin{gathered} P_{PV}(t) = ([P_{PV,STC} * \frac{G_T(t)}{G_{T_{STC}}} * (1 - \gamma * (T_m(t) - T_{mSTC}))] \\ * N_{PVs} * N_{PVp}), t = 1, ..., T \end{gathered} \tag{5}$$

$$\sum_{i=1}^{N} E_i * DSRRES_{t,i} \leq P_{PV}(t), t = 1, ..., T \tag{6}$$

The $DSESS_{t,i}$ refers to the scheduling matrix of energy storage system (ESS), defined as:

$$DSESS_{t,i} = \begin{cases} 1, & \text{if appliance } i \text{ is consuming power from ESS at time } t, \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

The $DSESS_{t,i}$ defines the scheduling of home appliances that utilize power from the ESS. In this work, ESS is composed by a system of batteries, connected to the photovoltaic panels (PV), installed in the consumer's house. The ESS acts as a storage of electrical energy generated by the PV system, as well as a source of power for the home appliances when the energy prices are high. Model of energy storage system are shown through (8)-(14) [26].

$$P_{ESS}(t) = E_S(t) - E_S(t-1), t = 1, ..., T \tag{8}$$

$$E_S^{min} \leq E_S(t) \leq E_S^{max}, t = 1, ..., T \tag{9}$$

$$E_S^{min} - E_S(0) \leq \sum_{k=1}^{t} (P_{ESS}(k)) \leq E_S^{max} - E_S(0), \quad t = 1, ..., T \tag{10}$$

$$E_S(0) = E_S(T) \tag{11}$$

$$-\omega_C^E * P_{ESS}(t) \leq P_{E-char}^{max}, t = 1, ..., T \tag{12}$$

$$\frac{P_{ESS}(t)}{\omega_D^E} \leq P_{E-disch}^{max}, t = 1, ..., T \tag{13}$$

$$\sum_{i=1}^{N} E_i * DSESS_{t,i} \leq P_{ESS}(t), t = 1, ..., T \tag{14}$$

where $E_S(t)$ is the energy stored in the battery at time *t*; $P_{ESS}(t)$ is the battery's output power at time *t*; E_S^{min} and E_S^{max} are the minimum/maximum battery stored energy's boundaries, respectively. (8) states that the output power of the battery can not be greater than the current stored energy. (9) shows that the energy in the batteries must be limited between the minimum and maximum levels to avoid lifetime reduction of the batteries. At each time interval t, the $P_{ESS}(t)$ must be between these limits. Charging and discharging powers at each time *t* are limited by the actual energy stored in the battery, as shown in (10). The initial and final state of the battery load must be the same as described by (11). The limitation on charging/discharging for the batteries in the ESS are shown in (12) and (13). (14) states that the consumption of energy provided by the ESS must be less than or equal to its output power.

The function $f2$ measures the inconvenience and evaluates how the optimized scheduling of home appliances can modify the satisfaction/comfort of the final consumer and is given by

$$Minimize \sum_{t=1}^{T} \sum_{i=1}^{N} (Incv_{t,i}^{hourly}(DSA_{t,i}) + Incv_{t,i}^{thermal}(DSA_{t,i})) \tag{15}$$

(15) evaluates the consumption cost associated with two types of inconvenient situations, previously defined by the consumer. The higher the cost calculated through (15), the greater the inconvenience, expressed in monetary values based on the energy price coming from the utility and in how far the scheduling is of the desired by the consumer. These situations are expressed through operating hours and thermal conditions that each appliance must meet, as defined by the consumer.

The inconvenience is defined in two ways: the hourly inconvenience and the thermal inconvenience. The hourly inconvenience calculates the electricity consumption-associated cost in which home appliances are used at inconvenient times, according to the operational profile defined by the consumer. Such profile is composed by two arrays, $Profile\_Time$ e $Profile\_Req$, that allow the home appliances operate with multiple starting/ending times. Each home appliance i has a $Size\_Profile_i$, which represents the number of different operating times defined for that specific home appliance. Based on that, the hourly inconvenience is defined by the $Incv_{t,i}^{hourly}(DSA_{t,i})$ function and is given by:

$$Incv_{t,i}^{hourly}(DSA_{t,i}) = \begin{cases} Pr_t * (ST_i^j - t) * DSA_{t,i}, & \text{if } t < ST_i^j, \\ 0, & \text{if } ST_i^j \leq t \leq ET_i^j, \\ Pr_t * (t - ET_i^j) * DSA_{t,i}, & \text{if } t > ET_i^j. \end{cases} \tag{16}$$

Where $j = 1, ..., Size\_Profile_i$.

The thermal inconvenience calculates the consumption cost at which the home appliances are used under inadequate/inconvenient thermal conditions as defined by the consumer. It's given by $Incv_{t,i}^{thermal}(DSA_{t,i})$ function, with the following configuration:

$$Incv_{t,i}^{thermal}(DSA_{t,i}) = \begin{cases} Pr_t * (Tem_t^{\underline{des}} - Tem_t^{in}) * DSA_{t,i}, & \text{if } Tem_t^{in} < Tem_t^{\underline{des}}, \\ 0, & \text{if } Tem_t^{\underline{des}} \leq Tem_t^{in} \leq Tem_t^{\overline{des}}, \\ Pr_t * (Tem_t^{in} - Tem_t^{\overline{des}}) * DSA_{t,i}, & \text{if } Tem_t^{in} > Tem_t^{\overline{des}}. \end{cases} \tag{17}$$

Where $Tem_t^{\underline{des}}$ and $Tem_t^{\overline{des}}$ are the min/max desired indoor temperature at time *t*, respectively; Tem_t^{in} is the indoor temperature at time *t*, calculated as follow [27]:

$$Tem_t^{in} = Tem_{t-1}^{in} + \alpha * (Tem_t^{out} - Tem_{t-1}^{in}) + \beta * DSA_t^i * E_i, t = 1, ..., T, i = 1, ..., N \tag{18}$$

Where Tem_t^{out} is the external temperature; α and β are thermal conditions surrounding the thermal home appliance. The function $f3$ measures the difference between the peak demand and the average demand, and evaluates how close are those two values. This indicates how "flattened" are the demand along the time horizon, which avoid the occurrence of rebound peaks. The formulation of $f3$ is:

$$Minimize(max(Cons) - mean(Cons))^2 \tag{19}$$

Where $max(Cons)$ and $mean(Cons)$ are, respectively, the peak demand and the average demand. $Cons$ is given by $DSA_{t,i} * E_i$, where E_i is the energy consumption of each home appliance per time interval.

With all objective functions defined, the best solution is one in which the home appliances are working as close as possible to the desired situation defined by the consumer and at the same time reduces the electricity consumption-associated cost and the peak-to-average demand difference. The closer the schedule is to the desired one, the better the solution.

B. NSGA-III

In this study, the Constrained NSGA-III, proposed in [22], was adapted to tackle the multi-objective price-based DR problem. Every chromossome is a combination of the three binary matrix presented in Section II (DSA, $DSRRES$ and $DSESS$) and represents a possible schedule in the problem.

The dimensionality of each matrix depends on the number of appliances N and the time horizon T.

The constrained NSGA-III was designed to face up to many objectives at the same time (more than three), besides handling constrained problems, and is similar to the original NSGA-II algorithm [28], despite significant changes in its selection operator. But, unlike NSGA-II, the maintenance of diversity among population members in NSGA-III is aided by supplying and adaptively updating a number of well-spread reference points [22].

III. Results and discussion

In this section, the results of computational simulations are presented in order to evaluate the performance of the proposed multi-objective optimization model of DR using the constrained NSGA-III optimization technique.

A. Case Study

In the simulation scenario, families composed of 02 adults without children were considered. The pattern of electrical energy consumption for each family was acquired through *Load Profile Generator (LPG)* [29] for 3 Brazilian families living in the cities of Brasília (DF), Florianópolis (SC) and João Pessoa (PB) located in the Center-West, South and Northeast regions of Brazil respectively.

A time horizon of T, with hourly discretization, was used in the computational simulations, which includes the days with highest and lowest electrical energy consumption for each family between January 1, 2016 and December 31, 2016. Is assumed that the entire scheduling time interval consists of 24 subintervals, that is, $t = \{1, 2, ..., 24\}$. Thus, the price of unit energy consumption in each time interval is based on the values of Portugal's Electricity Market (OMIE) to calculate the price of electricity for each hour, since Brazil does not use a DR program based on real-time electricity prices (RTP). The Home Energy management System (HEMS) proposed in [30] was used as an architecture in which the multi-objective DR model proposed in this paper is responsible for determining the load scheduling and the cycle of charge/discharge of ESS.

B. Simulation Results

In this work, we use the reference point scheme to found only a few solutions on a preferred part of the Pareto-Optimal front [22]. This scheme act as a way to represent consumer preferences in the optimization process, helping in the decision-making.

As defined in [22], a set of reference points (Rp) in the region of preference of consumer must be supplied. In addition, M extreme reference points $(1,0,0)^T, (0,1,0)^T, (0,0,1)^T$ are included, to make the normalization process to work well and make a total of $|Rp| + M$ reference points. As stated previously, twelve more extreme points (set Rp) are added to make a total of fifteen reference points. The crossover and mutation probability used were 0.6 and 0.1 respectively; Population had 16 chromosomes and the maximum number of iterations was 700.

TABLE I
OPTIMAL COST REDUCTION PER CITY

City	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
Brasília-DF	341.09	259.23	24.00
João Pessoa-PB	347.32	260.49	25.00
Florianópolis-SC	294.62	220.96	25.01

In Figure 1, the non-normalized Pareto-optimal solutions obtained are shown. These solutions were analyzed considering the energy consumption pattern of each family, obtained through LPG.

Table I presents the simulations results obtained for each family, taking into account the extreme point related to the objective of cost minimization, that is related to the Pareto-optimal solution for this objective. Thus, it is possible to observe that the family resident in the city of Florianópolis-SC obtained the best result in relation to the total reduction of electricity consumption cost, going from R$ 294.62 to R$ 220.96, totaling a decrease of 25.01 %.

Table II presents the simulations results obtained for each family, taking into account the extreme point related to the objective of inconvenience minimization, which is related to the Pareto-optimal solution for this objective. Thus, it is possible to observe that the family resident in the city of João Pessoa-PB obtained the lowest inconvenience-associated cost, with R$ 0.29.

TABLE II
OPTIMAL INCONVENIENCE PER CITY

City	Inconvenience (R$)
Brasília-DF	0.3
João Pessoa-PB	0.29
Florianópolis-SC	0.3

The labeled solution as "A" in the Figure 1 is the solution closest to the optimal point (0, 0). This solution presents the best tradeoff between the values of the two objectives formulated in the DR problem presented in this work. The cities of João Pessoa-PB and Florianópolis-SC obtained equal results in the cost minimization objective, with a total decrease of 24.1 % on consumption cost, while in the objective of minimizing inconvenience, the city of João Pessoa-PB obtained the lowest inconvenience-associated cost, with R$ 0.81. The results obtained in the A-solution are presented in Tables III and IV.

TABLE III
A-SOLUTION COST REDUCTION PER CITY

City	Cost Without DR (R$)	Cost With DR (R$)	Reduction (%)
Brasília-DF	341.09	259.62	23.9
João Pessoa-PB	347.32	260.88	24.1
Florianópolis-SC	294.62	221.35	24.1

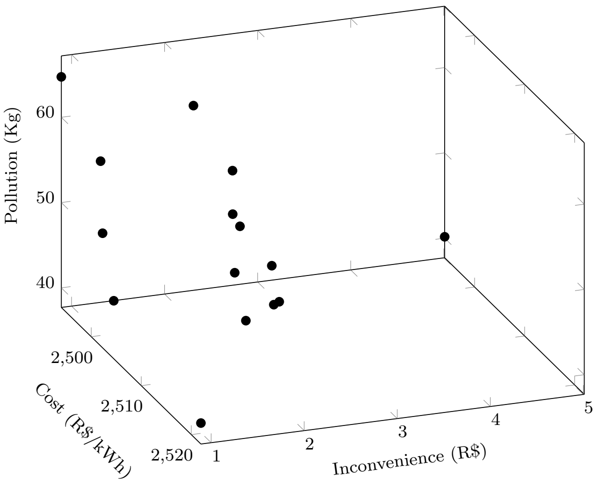

Fig. 1. Non-normalized Pareto-optimal solutions.

TABLE IV
A-SOLUTION INCONVENIENCE PER CITY

City	**Inconvenience (R$)**
Brasília-DF	0.82
João Pessoa-PB	0.81
Florianópolis-SC	0.82

C. Rebound peak impact

The impact of the rebound peak objective function on the results obtained in the simulation was also analyzed. A scenario without the function $f3$ was simulated. The energy consumption and the peak-to-average demand difference, for the day with the highest energy consumption in each case, were compared. Table V shows that, when the DR algorithm runs without considering rebound peaks, it creates a new peak, higher than those obtained in the scenario without DR, guided by the minimization cost objective. When the $f3$ function acts, it avoids this situation, and as the average consumption does not change, the peak-to-average demand difference is minimized.

D. Statistical Analysis

The results from the experiments of home appliance scheduling were analyzed by three performance metrics: Diversity [31], Coverage and Hypervolume [32], to evaluate the determining the overall performance of the used technique. Simulations with the R-NSGA-II [33] were used to calculate the Coverage and Hypervolume metrics. The R-NSGA-II is compared to the NSGA-III optimization technique, and both

TABLE V
REBOUND PEAK IMPACT PER CITY

City	Brasília-DF	João Pessoa-PB	Florianópolis-SC
Peak consumption without DR (Kw)	1,1338	1,2439	1,6265
Peak consumption without f3 (Kw)	1,4332	1,8439	1,9832
Peak consumption with f3 (Kw)	0,9942	0,8255	1,2360

TABLE VI
STATISTICAL ANALYSIS.

Algorithm	Metric	Min	Max	Average	Standard Deviation
NSGA-III	Spacing	18.21	22.30	19.46	1.02
R-NSGA-II		12.25	18.25	14.98	1.05
NSGA-III R-NSGA-II	C(A, B)	1	1	1	0
NSGA-III R-NSGA-II	C(B, A)	0	0	0	0
NSGA-III	HV	0.91	0.92	0.906	0.01
R-NSGA-II		0.72	0.83	0.77	0.02

were performed 1000 times to reduce the impact of their stochastic nature and to obtain the values to be used in the statistical analysis.

1) Statistical Results: The results of the NSGA-III optimization technique were compared with the values from the R-NSGA-II in order to validate the correctness of the algorithm (*sanity check*). The values of the spacing metric showed that the NSGA-III (minimum 18.21 and maximum 22.3) had a greater diversity of solutions than the R-NSGA-II (minimum 12.25 and maximum 18.25) Therefore, the NSGA-III had a better coverage of the search space, and this translates into a better comprehension of the objectives considered in the problem.

In the metric C, the values obtained for both $C(A, B)$ and $C(B, A)$ indicate that, in all cases, the Pareto frontier solutions found by the NSGA-III completely dominated the frontier solutions of Pareto found by R-NSGA-II. This result shows that the NSGA-III presents better solutions than the R-NSGA-II, considering the Pareto frontier of both techniques.

Additionally, the analysis of the Hypervolume values indicates a significantly better general performance of NSGA-III (minimum 0.91 and maximum 0.92) in relation to R-NSGA-II (minimum 0.72 and maximum 0.83). This information, as previously mentioned, reflects the better performance, in terms of convergence and extension, of the solution considering the search space [32]. Therefore, both the NSGA-III and R-NSGA-II enable the load scheduling to provide a reduction of electricity costs, as well as minimize the inconvenience caused to the end consumers in an appropriate manner. Table VI shows the statistical values for the simulations.

CONCLUSIONS

This paper proposes a multi-objective DR optimization model to manage the scheduling of home appliances with various categories in a microgrid environment, aiming at minimizing the electricity consumption-associated cost, as well as minimizing the inconvenience (dissatisfaction/discomfort) of end consumers, and the rebound peak occurrences considering renewable energy resources (RRES) and an energy storage system (ESS). The scheduling of home appliances on smart grids allows the EPS to be more efficient and effective, because problems such as power interruptions during peak demands can be minimized. Thus, DR plays a key role in managing energy consumption in order to avoid overhead as well as reduce the electricity consumption-associated cost to end consumers.

The performance of the proposed DR optimization model was evaluated through simulations. First, the efficiency for cost minimization associated with the consumption of electrical energy as well as inconvenience (dissatisfaction/discomfort) minimization of end consumers, considering some preference points given by the consumer was analyzed. In addition, the multi-objective model was adapted to handle the same DR problem without considering rebound peak occurrences, in order to verify the influence on the electricity consumption. Next, through the diversity, coverage and hypervolume metrics, a statistical analysis was made to validate the proposed technique performance and accuracy, as seen in Table VI.

Future research could further improve in several directions. One possibility would be to include electric vehicles and more renewable resources for the electrical energy generation in the optimization model. Another direction could be to minimize environmental pollution as an objective in the optimization model. A third option is to implement the proposed model in an in-home display so as to use the proposal in an edge computing scenario.

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