A reliability-and-cost-based fuzzy approach to optimize preventive maintenance scheduling for offshore wind farms

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Abstract

We study the preventive maintenance scheduling problem of wind farms in the offshore wind energy sector which operates under uncertainty due to the state of the ocean and market demand. We formulate a fuzzy multi-objective non-linear chance-constrained programming model with newly-defined reliability and cost criteria and constraints to obtain satisfying schedules for wind turbine maintenance. To solve the optimization model, a 2-phase solution framework integrating the operational law for fuzzy arithmetic and the non-dominated sorting genetic algorithm II for multi-objective programming is developed. Pareto-optimal solutions of the schedules are obtained to form the trade-offs between the reliability maximization and cost minimization objectives. A numerical example is illustrated to validate the model.

Keywords: Offshore wind energy, Preventive maintenance scheduling, Fuzzy chance-constrained programming, Fuzzy multi-objective programming, Reliability, Maintenance cost

1. Introduction

By the end of 2017, Europe leaded the global offshore energy market, with 83.9% share of the total installed capacity of 18,814 MW from 4,149 grid-connected wind turbines of 92 offshore wind farms in 11 countries (Global Wind Energy Council 2018; WindEurope 2018). The UK has the largest amount representing 43.3%, followed by Germany (Schiermeier 2013). The total European offshore wind capacity is forecast at 25 GW by 2020 and 70 GW by 2030 (by then 7-11% of

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the EU's electricity demand is produced by offshore wind). Besides, the Chinese offshore wind energy market began in 2016 (14.9% market share) (Cyranoski 2009; Davidson et al. 2016; Yuan 2016), followed by Vietnam, Japan, South Korea and the US (Russo 2014). With the growing engagement in the offshore wind industry worldwide, it is natural to investigate the operations and maintenance problems of the offshore wind farms. Given the difficulty in the techniques, availability, and accessibility due to the uncertain ocean wind environment, the maintenance costs for the offshore wind farms can form up to 25-30% of the energy cost, and is typically estimated at five to ten times of the onshore maintenance cost (Pattison et al. 2016). Once a failure occurs, a longer system downtime, and more loss in revenue follow. Therefore, it is useful to study the maintenance problem of the offshore wind farms.

In the literature, maintenance is classified as either *corrective maintenance* (CM) or *preventive maintenance* (PM). The former is usually performed after a system failure or breakdown while the latter corresponds to the scheduled actions which are performed when the system is still operational. The research question sought in this paper is to determine the best PM scheduling of the offshore wind farms operating in an uncertain environment. The goal of PM in the offshore wind power system is to avoid or mitigate a failure possibility caused by fatigue, cumulative damages and corrosion resistance degradation, i.e., maintain the reliability of the system at an operationally acceptable level. PM is also able to prevent the occurrence of faults effectively either before they occur or before they develop into major defects. Practically, the scheduling of PM is to determine acceptable arrangements of the downtime for the offshore wind turbines.

The maintenance scheduling problem is well studied in the electricity sector (Froger et al. 2016; Petchrompo and Parlikad 2019; Salameh 2018). Beyond the literature of operations and maintenance optimization of offshore wind energy, Zhong et al. (2018) initiated the PM scheduling study of offshore wind farms in a deterministic setting by giving the system reliability and maintenance cost objectives and constraints a more sound definition comparing with more conventional approaches existing in the corresponding literature. In this regard, a non-linear multi-objective programming model is built to optimize the two objectives simultaneously and a NSGA-II is employed to solve the model. The paper calls for awareness of considering fully the peculiarity of maintenance in different application scenarios (here it refers to the offshore wind farms) and redefining the maintenance model as needed.

In view of the uncertain nature of the marine environment, it would be insufficient if we only see it as deterministic. The problem modeling and optimization approaches have substantial differences when discussing in a deterministic or uncertain environment. As a natural successor, a further extension and improvement of the Zhong et al. (2018)'s study is thereby motivated to enhance our understanding of this real-life application. Thus, we intend to develop a method of PM scheduling more applicable to the realistic (uncertain) operating sea environment. An immediate question arises: "what is the way that we depict an uncertain marine environment?" We specifically consider it as fuzzy due to the fact that the available collected, stored and manipulated data may be tainted with imprecision and uncertainty under the impact of inherently variable and complex marine environment. The fuzzy set theory has the strength to handle and represent such data imprecision, which allows us to model and make decisions based on incomplete data (Baños et al. 2011; Coşgun et al. 2014; Damousis et al. 2004; Dubois and Prade 1997).

Thus, in this paper, we aim to extend the study of the PM scheduling problem for offshore wind farms in a fuzzy setting utilizing modeling and optimization techniques. Thus, we formulate a novel model and design an associated solving method. Our objective is to propose a generic approach as a guidance for decision-makers. It is easy to compare, analyze and select the expected results of the model to support PM decisions. The main contributions of this paper include:

(i) Treating the PM scheduling problem for offshore wind farms in a fuzzy setting. It is an upgrade and expansion comparing with Zhong et al. (2018) discussing the PM scheduling in a deterministic framework. Specifically, a *fuzzy chance-constrained programming* (FCCP) approach integrating the principles of the expected value model and the chance-constrained programming is employed. The wind speed, power demand and generation, and the maintenance cost in the problem are defined as fuzzy variables (Baños et al. 2011; Coşgun et al. 2014; Damousis et al. 2004), which are better suited to the offshore wind context. Since there exist considerable uncertainty and asperity in the marine environment and energy market which influence the accuracy of the data collected and predicted, the credibility measure based on fuzzy set theory can leverage its strength in estimating this type of data uncertainty.

(ii) Proposing a fuzzy multi-objective programming model to optimize the reliability and cost objectives simultaneously. Although reliability and cost are two conventional criteria for defining the objectives of the maintenance optimization problem, in most cases for power systems, the two targets are treated separately, i.e., one as objective and the other as a constraint in accordance with the different emphases of the decision-makers. Only in Zhong et al. (2018), to the authors' knowledge, the two goals have been considered at the same time for maintenance scheduling of an offshore wind system handling it as a deterministic multi-objective programming problem. Therefore, this paper transfers the previous set-up into a fuzzy framework to model uncertainty.

(iii) Formulating new definitions of the reliability and cost criteria, as well as constraints. For the reliability criterion, Zhong et al. (2018) refined the power reserve ratio definition, which is one of the two prevailing reliability definitions, by proposing the attainment exponent to improve the defect of ignoring the benefits from PM. In this paper, we keep the same idea, i.e., the power reserve ratio is adopted as the base of our new definition to measure the customer satisfaction with the power supply, and an attainment exponent is introduced to evaluate the sustainability of a wind farm. But not only that, therein, we innovatively consider the uncertainties in the market power demand and the piecewise generated power as fuzzy, where the ambiguity of power production is due to the relationship with the fuzzy offshore wind speed. The relationship between the wind regime and the generated power has not been examined so far in the wind farm maintenance literature.

On the cost criterion, we first refer to the maintenance cost components of the offshore wind farms devised in Zhong et al. (2018). Then, we refine the cost definition by proposing time-dependent fuzzy exponential weights for each cost item to depict the cost trend over time so that the cost can be found more reasonably for a volatile marine wind environment. What is more, in this paper, the constraints of keeping sufficient net power reserve are modified accordingly to accommodate the uncertainties therein, by using the same fuzzification way of handling the reliability criterion.

(iv) Developing a 2-phase solution framework to solve the proposed fuzzy multi-objective non-linear chance-constrained programming model for the PM scheduling of offshore wind farms. In our solution framework, Phase I employs the operational law which uses accurate fuzzy arithmetic instead of fuzzy approximation or simulation (Zhou et al. 2016) for simplifying the FCCP in the model so as to convert it into an equivalent deterministic programming that already has mature solving methods. Subsequently, the treated model proceeds to Phase II, which uses the designed *non-dominated sorting genetic algorithm II* (NSGA-II (Deb et al. 2002)) to deal with the remaining *multi-objective non-linear programming* (MONLP) to obtain a set of Pareto-optimal solutions to support the decision-making on the schedule. Whereas, Zhong et al. (2018) only employed the NSGA-II (same conception as Phase II in this paper) to solve their model which is deterministic and less complicated.

(v) Considering the PM and CM costs integrally to obtain the optimal solution and weigh cost performance for supporting the decision-making. We make our approach more easy-to-use and straightforward for decision-makers, as the results derived can be well-interpreted and simply compared. Thus, if decision-makers know what a certain reliability value or one percent improvement in reliability mean in cost wise, they can select and determine a maintenance policy more sensibly according to actual conditions given the expected outputs of the model. It is a tangible improvement comparing with the decision-making guidance in Zhong et al. (2018).

The rest of the paper is organized as follows: Section 2 reviews the main parts of the vast corresponding literature focusing mostly to the general class of power systems. Section 3 constructs a fuzzy multi-objective non-linear chance-constrained programming model with reliability and cost criteria to schedule the PM for offshore wind farms in a fuzzy environment. Section 4 builds the 2-phase solution framework integrating the operational law and NSGA-II to solve the proposed model. Section 5 validates the effectiveness and performance of the model and solution method by illustrating a PM scheduling case of the offshore wind farms as a numerical example. Section 6 concludes the paper. Appendix A introduces the credibility theory and the operational law employed to handle the fuzzy programming.

2. Literature review

In this section, the literature regarding the motivation and main contributions of this paper are carefully considered covering operations problems and maintenance of power systems except for the offshore wind farms.

(1) Operations and maintenance optimization of offshore wind energy:

In the offshore wind energy sector, a few studies have investigated the operations optimization problems. In particular, for the PM problem, Li et al. (2016) developed a decision support system for maintenance planning in offshore wind farms so as to reduce the lifecycle maintenance costs. Two optimization modules, deterministic and stochastic, are constructed for different failure descriptions. Pattison et al. (2016) presented a novel architecture and system comprising three integrated modules for intelligent condition monitoring, reliability and maintenance modelling, and maintenance scheduling that provide a scalable solution for performing dynamic, efficient and cost-effective PM management within the offshore wind power generation sector. Irawan et al. (2017a) proposed a mixed integer linear programming (MILP) optimiser based on the Dantzig-Wolfe decomposition to find the optimal schedule for maintaining offshore wind turbines and the optimal routes for the crew transfer vessels to service the turbines along with the number of technicians required for each vessel so as to minimise the maintenance cost. Similarly, a stochastic fleet size and mix model targeting the minimum cost for maintenance operations at the offshore wind farms was studied in Gundegjerde et al. (2015). Sarker and Faiz (2016) formulated a maintenance cost model for offshore wind turbine components following a multi-level opportunistic PM strategy that considers preventive replacement and maintenance.

Further, Ursavas (2017) solved the offshore wind farm installation planning problem which involves determining the lease period of the offshore installation vessels and the scheduling of the operations to build a wind farm. Decisions are made under the disruptions due to the uncertain wind condition using Benders decomposition. Irawan et al. (2017b) investigated a layout problem for an installation port of an offshore wind farm based on minimising the transportation cost. Two MILP models are formulated to configure the optimal port layout, whose shape can be treated as either a convex or concave polygon.

(2) Fuzzy theories in operations and maintenance of power systems:

Fuzzy techniques have been applied to maintenance problems for general power systems (Dahal et al. 1999; El-Sharkh et al. 2003; Leou 2001; Liu et al. 2010; Sergaki and Kalaitzakis 2002; Volkanovski et al. 2008), and especially on the coordinated maintenance scheduling with cost minimisation, reliability maximisation, and risk minimisation as multi-objective criteria, and fuzzy learning-based optimisation for a composite power system (Subramanian et al. 2015).

Further, fuzzy methods have been used on other operational problems of the wind farms. For example, Siahkali and Vakilian (2010) developed a fuzzy optimization-based approach to the scheduling problem for wind farms, in which the load, reserve and available wind power generation are treated as fuzzy. Thereafter, they proposed an interval type-2 fuzzy modeling approach to the same problem for wind farms in Siahkali and Vakilian (2011). Shafiee (2015) built a fuzzy analytic network process (ANP) model to select the most appropriate risk mitigation strategy for offshore wind farms. Likewise, Yeh and Huang (2014) examined the factors in determining the location of wind farms. The fuzzy Decision Making Trial and Evaluation Laboratory (DEMATEL) and ANP approaches are applied to find the correlations among the dimensions and the relative weights of the criteria, respectively. Wang and Singh (2008) formulated a bi-objective economic power dispatch model considering wind penetration, which treats the operational cost and system risk as conflicting objectives. Different fuzzy membership functions are used to indicate the security level in terms of wind penetration and wind power cost. A multi-objective particle swarm optimization algorithm is then designed to develop the power dispatch schemes. Similarly, Aghaei et al. (2013), Azizipanah-Abarghooee et al. (2012), and Bahmani-Firouzi et al. (2013) investigated the multi-objective economic emission dispatch problem which simultaneously minimizes the electrical energy costs and emissions by incorporating wind power generators. Fuzzy-based clustering and adaptive techniques are used to solve the optimization models.

(3) Multi-objective optimization in maintenance of power systems:

Without fuzzy consideration, some papers have already studied the maintenance scheduling problem for general power systems using multi-objective optimization. Leou (2006) combined a genetic algorithm (GA) with simulated annealing to solve the unit maintenance scheduling problem with the fitness maximization objective composed by the reliability and cost indices. Yang et al. (2008) used a Markov model to handle the reliability and cost objectives, and Yang and Chang (2009) rebuilt the same model for the energy not served, and the operation and expected failure cost objectives. Both models are solved by the NSGA-II, as with the imperfect PM maintenance model optimizing system availability and cost in Wang and Pham (2011). Zhan et al. (2014) designed a multi-objective generation maintenance scheduling model, in which profit maximization, reliability maximization, and generation cost minimization are optimized by a group search optimizer with multiple producers. Hadjaissa et al. (2016) conducted a modified GA based bi-objective optimization of PM scheduling for power systems to find a trade-off between the makespan and training time of the operators. On fuzzy multi-objective optimization, only Subramanian et al. (2015) used the cost, reliability and risk criteria to arrange the maintenance tasks for a composite power system.

(4) Reliability and cost criteria definitions in maintenance of power systems:

In the corresponding literature, the reliability criterion is defined either as the net to gross power reserve ratio (Canto 2011; Canto and Romero 2013; Conejo et al. 2005), or as the sum of the squares of the net power reserve to assess the resource utilization (Ben-Daya et al. 2000; Dahal et al. 1999; Dahal and Chakpitak 2007; Dahal and Galloway 2007; Ekpenyong et al. 2012). The former is maximized and the latter minimized to pursue the highest reliability objective.

The maintenance cost components of Zhong et al. (2018) and this paper follow the commonly-used economic targets in the maintenance scheduling literature, such as those initiated by Canto (2008), Dahal et al. (2015), Dalgic et al. (2015), Ding and Tian (2012), Gundegjerde et al. (2015), Zhang et al. (2013) among others.

3. Optimization model formulation

We now formulate the multi-objective non-linear FCCP model with the reliability maximization and cost minimization objectives under realistic constraints to obtain the PM schedules for the offshore wind farms in a fuzzy environment.

3.1. Notations

Our problem is to assign the maintenance work of the offshore wind farm containing m turbines into n periods. The indices, parameters, and decision variables are introduced in Table 1.

3.2. Fuzzy system reliability maximization objective

By the reliability of the offshore wind farm system, we mean the customer satisfaction from sufficient power reserve and the sustainability effects to the wind farm system. Although PM decreases power generation due to the turbine downtime, it can fight against corrosion and degradation of the turbines, and mitigates the risk of serious breakdowns in the entire grid.

In our reliability criterion, the uncertainty in the market power demand and the piecewise generated power are considered as fuzzy, and the ambiguity of the power production is incurred by the relationship with the fuzzy offshore wind speed. The fuzzy system reliability $\tilde{R}$ is defined as the average of the fuzzy period reliabilities $\tilde{r}_t$. In the period reliability $\tilde{r}_t$, the fuzzy net power reserve $\tilde{e}_t$ to the fuzzy gross power reserve $\tilde{E}_t$ ratio is the base to measure the customer satisfaction with the power supply, and the attainment exponent s_t is introduced to evaluate the wind farm

Table 1: Notations of PM scheduling problem for offshore wind farms in fuzzy environment

m	number of turbines in wind farm	C^{F^V}	unit fixed cost (€) of vessels
i	index of offshore wind turbines	C^{F^H}	unit fixed cost (€) of helicopters
n	number of periods in time horizon	$C_i^{S^V}$	unit vessel transport cost (€) for TR_i
t	index of time periods	$C_i^{S^H}$	unit helicopter transport cost (€) for TR_i
TR_i	turbine i	V_i	vessel demand for maintaining TR_i
PR_t	time period t	H_i	helicopter needed for maintaining TR_i
$\tilde{R}$	system reliability (%) of wind farm	LV_t	permitted moving vessels in PR_t
$\tilde{r}_t$	reliability (%) in PR_t	LH_t	permitted moving helicopters in PR_t
s_t	attainment exponent affecting power demand satisfaction in PR_t, $s_t \geq 0$	C_i^{CRM}	customer relationship management cost (€) for TR_i
$\tilde{E}_t$	gross power reserve (MWh) in PR_t	$\tilde{\lambda}_{i,t}^M$	weight exponent of C_i^M for TR_i in PR_t
$\tilde{e}_t$	net power reserve (MWh) in PR_t	$\tilde{\lambda}_{i,t}^{EQ}$	weight exponent of C_i^{EQ} for TR_i in PR_t
$\tilde{d}_t$	power (MWh) required in PR_t	$\tilde{\lambda}_{i,t}^I$	weight exponent of C_i^I for TR_i in PR_t
$\tilde{p}_{i,t}$	power (MWh) generated by TR_i in PR_t	$\tilde{\lambda}_{i,t}^{EM}$	weight exponent of C_i^{EM} for TR_i in PR_t
p_R	rated power (MW) of turbines	$\tilde{\lambda}_{i,t}^T$	weight exponent of C_i^T for TR_i in PR_t
v_C	cut-in wind speed (m/s) of turbines	$\tilde{\lambda}_{i,t}^A$	weight exponent of C_i^A for TR_i in PR_t
v_R	rated wind speed (m/s) of turbines	$\tilde{\lambda}_{i,t}^{CRM}$	weight exponent of C_i^{CRM} for TR_i in PR_t
v_F	cut-out wind speed (m/s) of turbines	LT_t	turbine maintenance capacity in PR_t
$\tilde{v}_{i,t}$	wind speed (m/s) TR_i gets in PR_t	u	time coefficient (conversion into hour)
U	time period set not allowed for maintenance	GHG	greenhouse gas emission standard regulated by industry (kg)
$\tilde{C}_{i,t}$	maintenance cost (€) for TR_i in PR_t	z_i	distance (km) from shore to TR_i
C^{M^V}	vessel manpower cost (€)	q^V	vessel gas emission (kg/kg·km)
C^{M^H}	helicopter manpower cost (€)	q^H	helicopter gas emission (kg/kg·km)
C^{M^L}	onshore manpower cost (€)	$\bar{w}$	average weight of employee (kg)
M_i^V	vessel manpower demand for TR_i	EQ_i^V	equipment (kg) on vessels for TR_i
M_i^H	helicopter manpower demand for TR_i	EQ_i^H	equipment (kg) on helicopters for TR_i
M_i^L	onshore manpower demand for TR_i	AM_t	number of available manpower in PR_t
C_i^M	total manpower cost (€) for TR_i	AV_t	number of available vessels in PR_t
C_i^{EQ}	equipment cost (€) for TR_i	AH_t	number of available helicopters in PR_t
C_i^I	infrastructure cost (€) for TR_i	Ψ_t^{-1}	inverse credibility distribution of $\tilde{d}_t$
C_i^T	total transport cost (€) of TR_i	$\Upsilon_{i,t}^{-1}$	inverse credibility distribution of $\tilde{p}_{i,t}$
C_i^A	adjustment cost (€) for TR_i	$\Phi_{i,t}^{-1}$	inverse credibility distribution of $\tilde{\lambda}_{i,t}$
C_i^{EM}	environmental monitoring cost (€) for TR_i	α_t	confidence level supply and demand chance constraints hold in PR_t
L_i	maintenance deadline of TR_i (PR_{L_i})	$x_{i,t}$	0-1 decision variable denoting maintenance status of TR_i in PR_t
LP_i	maintenance duration of TR_i	$b_{i,t}$	0-1 decision variable denoting start state of TR_i in PR_t

* Variables with tilde denote triangular fuzzy variables.

sustainability effects as,

$$\tilde{r}_t = (\tilde{e}_t/\tilde{E}_t)^{s_t}, \tag{1}$$

in which $\tilde{E}_t$ follows from deducting the fuzzy power demand from the generated amount, i.e.,

$$\tilde{E}_t = \sum\nolimits_{i=1}^{m} \tilde{p}_{i,t} - \tilde{d}_t, \tag{2}$$

and $\tilde{e}_t$ needs to subtract the shutdown loss of the energy production due to maintenance as

$$\tilde{e}_t = \sum\nolimits_{i=1}^{m} \tilde{p}_{i,t}(1 - x_{i,t}) - \tilde{d}_t. \tag{3}$$

Actually in this paper, as it was presented in details in Zhong et al. (2018), the use of an isoelastic (power) function, Eq. (1), to model the behavioral attitude of our treatment is also incorporated. So the expanded form of $\tilde{r}_t$ in Eq. (1) is given by (4),

$$\tilde{r}_t = \left[\frac{\sum_{i=1}^{m} \tilde{p}_{i,t}(1 - x_{i,t}) - \tilde{d}_t}{\sum_{i=1}^{m} \tilde{p}_{i,t} - \tilde{d}_t} \right]^{s_t}. \tag{4}$$

The fuzzy offshore wind speed and the technical characteristics of the installed wind turbines have a large impact on the power generation $\tilde{p}_{i,t}$ in Eq. (4) (see Fig. 1). Fig. 1 is a schematic plot showing a typical power curve of a wind turbine generator. A wind turbine starts to generate power at the cut-in wind speed v_C and is shut down for safety and damage-prevention reasons at the cut-out wind speed v_F. The rated power p_R is generated when the wind speed is between the rated speed v_R and the cut-out speed v_F[1]. There is a non-linear relationship between the power generated and the wind speed while the speed is within the cut-in speed v_C and the rated speed v_R (Karki et al. 2006). Hence, a fuzzy quadratic model of the power curve of wind turbine is established to express their complex relationship based on its original definition in Pallabazzer

[1] The rated power, cut-in wind speed, rated wind speed and cut-out wind speed (constant parameters) are engineering characteristics designed for a specific turbine model.

(1995),

$$\tilde{p}_{i,t} = \begin{cases} 0, & \mathbb{E}[\tilde{v}_{i,t}] \leq v_C \\ u \cdot p_R \dfrac{\tilde{v}_{i,t}^2 - v_C^2}{v_R^2 - v_C^2}, & v_C < \mathbb{E}[\tilde{v}_{i,t}] < v_R \\ u \cdot p_R, & v_R \leq \mathbb{E}[\tilde{v}_{i,t}] \leq v_F \\ 0, & \mathbb{E}[\tilde{v}_{i,t}] > v_F, \end{cases} \tag{5}$$

where $\tilde{v}_{i,t} = (y_{i,t}^L, y_{i,t}^C, y_{i,t}^R)$ (m/s) is the wind speed, depicted by a triangular fuzzy variable because of the difficulty in predicting the uncertain speed TR_i receives in PR_t, p_R (MW) is the rated power of the turbine, u is a time coefficient to convert time into hours to calculate the energy, and v_C, v_R and v_F (m/s) are the cut-in, rated and cut-out wind speed of the turbine, respectively. As the fuzzy wind speed $\tilde{v}_{i,t}$ cannot be compared with the deterministic technical parameters v_C, v_R and v_F, here we specify a deterministic variable $\mathbb{E}[\tilde{v}_{i,t}]$, the expected value of the wind speed $\tilde{v}_{i,t}$ to segment the domain of definition. For example, when the value of $\mathbb{E}[\tilde{v}_{i,t}]$ lies in the interval $[v_R, v_F]$, the wind power output $\tilde{p}_{i,t}$ is equal to the energy used at the rated power p_R over time.

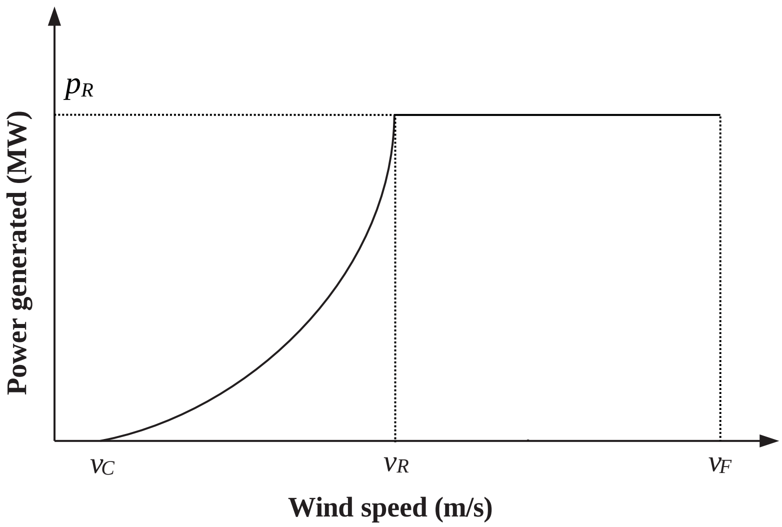


Fig. 1: Offshore wind power output

$\tilde{r}_t$ is affected by $\tilde{e}_t/\tilde{E}_t$, whose lower bound is that the net power generated must be enough to meet the customer electricity requirement when some turbines are under maintenance, i.e., $\tilde{e}_t = 0,\ \tilde{e}_t/\tilde{E}_t = 0,\ \tilde{r}_t = 0$. The upper bound is such that the net power reserve equals to the gross power reserve when all turbines are running, i.e., $\tilde{e}_t/\tilde{E}_t = 1,\ \tilde{r}_t = 1$. Thus, $\tilde{r}_t$ tends to 0 from 1 with the attainment exponent $s_t \in [0, +\infty)$ increasing, based on the properties of the exponential function. s_t gives $\tilde{e}_t/\tilde{E}_t$ three effects in the different value ranges:

(1) *Positive* effect: $\mathbb{E}[\tilde{r}_t] = \mathbb{E}[(\tilde{e}_t/\tilde{E}_t)^{s_t}] > \mathbb{E}[\tilde{e}_t/\tilde{E}_t]$, when $s_t \in [0, 1)$.

Maintenance can repair the wind farm system, recovering it from the deterioration caused by a volatile marine environment. The relationship between the expected values in the positive effect can be deduced from Eq. (A.9) easily, hence it is omitted here.

(2) *Neutral* effect: $\mathbb{E}[\tilde{r}_t] = \mathbb{E}[(\tilde{e}_t/\tilde{E}_t)^{s_t}] = \mathbb{E}[\tilde{e}_t/\tilde{E}_t]$, when $s_t = 1$.

The impacts of the maintenance and the degeneration are about the same. Maintenance will not significantly enhance the mechanical properties of the system, but only prevents it from further damage. The system in PR_t only needs moderate sustainability and reliability.

(3) *Negative* effect: $\mathbb{E}[\tilde{r}_t] = \mathbb{E}[(\tilde{e}_t/\tilde{E}_t)^{s_t}] < \mathbb{E}[\tilde{e}_t/\tilde{E}_t]$, when $s_t \in (1, +\infty)$.

The damage caused is serious and cannot be resolved thoroughly though the system is maintained. Any performance degradation leads to the risk of a shortage in power supply, power fault or collapse. So the system in PR_t has weaker sustainability and lower reliability than usual. Thus, $\tilde{R}$ can be defined by averaging $\tilde{r}_t$ as

$$\tilde{R} = \sum\nolimits_{t=1}^{n} \frac{1}{n} \tilde{r}_t, \tag{6}$$

in which the weight coefficient $1/n$ of $\tilde{r}_t$ is used to normalize $\tilde{R}$ into the range $[0, 1]$. From Eqs. (4) and (5), $\tilde{R}$ is equivalent to

$$\tilde{R} = \sum_{t=1}^{n} \frac{1}{n} \left(\frac{\tilde{e}_t}{\tilde{E}_t} \right)^{s_t} = \sum_{t=1}^{n} \frac{1}{n} \left[\frac{\sum_{i=1}^{m} \tilde{p}_{i,t}(1 - x_{i,t}) - \tilde{d}_t}{\sum_{i=1}^{m} \tilde{p}_{i,t} - \tilde{d}_t} \right]^{s_t}, \tag{7}$$

where $\tilde{p}_{i,t}$, and $\tilde{d}_t$, $i = 1, 2, \ldots, m$, $t = 1, 2, \ldots, n$, are defined by independent triangular fuzzy variables.

Notably, since n period reliabilities $\tilde{r}_t$ constitute the system reliability $\tilde{R}$, n attainment exponents s_t need to be settled on the basis of the above three effects. As it is difficult to collect the exact data of the effects due to the unknown degradation status and the maintenance capability especially for newly grid-connected offshore wind farms, a feasible scheme is to draw support from the decision-maker's experience. Thus, in what follows, we test some predefined behavioral attitudes of the decision-makers. Obviously, the proposed four categories, *"fully rational"*, *"optimism* *biased"*, *"wait-and-see attitudes"* and *"pessimism biased"* are initiating and inspiring, rather than exhaustive and conclusive for the research on maintenance, and more generally speaking, in the behavioral approach of the reliability index and our multi-objective constrained optimization problem. So, let us define briefly the four categories of attitudes (for more details, see Zhong et al. 2018):

(1) When the decision-makers are *fully rational*, all three effects appear in sequence over time, i.e., $s_1, s_2, \ldots, s_n$ are selected from the three sets $[0, 1)$, $\{1\}$, $(1, +\infty)$.

(2) When decision-makers are *optimism biased*, they are inclined to believe that maintenance can overcome the deterioration in all periods, and the system reliability remains at a high level. This suggests that all s_t are chosen from the interval $[0, 1)$.

(3) When decision-makers adopt a *wait-and-see attitude*, they think that effort of the maintenance and the deterioration can be perceived as balanced, so all s_t equal to 1, i.e., no more exponents exist.

(4) When the decision-makers are *pessimism biased*, the negative effects take up entire periods owing to the degradation and risks in a severe marine environment, so much so that even maintenance cannot guarantee or improve system stability. Now, all s_t can be picked from the interval $(1, +\infty)$.

In sum, the first objective function of our model is on fuzzy system reliability maximization:

$$\max \tilde{R} = \max_{\boldsymbol{X}} \sum_{t=1}^{n} \frac{1}{n} \left[\frac{\sum_{i=1}^{m} \tilde{p}_{i,t}(1 - x_{i,t}) - \tilde{d}_t}{\sum_{i=1}^{m} \tilde{p}_{i,t} - \tilde{d}_t} \right]^{s_t}, \tag{8}$$

in which $\tilde{p}_{i,t}$ is further defined by Eq. (5).

3.3. Fuzzy maintenance cost minimization objective

The maintenance cost minimization objective refers to the commonly-used maintenance, start-up, fixed, variable, and opportunity cost fitted into the offshore wind energy context to design a new cost criterion with 7 components (Zhong et al. 2018). Next, the cost criterion is refined by proposing time-dependent fuzzy exponential weights for each cost item to depict the cost trend so that maintenance cost can be evaluated more reasonably in the complex and volatile ocean environment.

The 7 cost components for the PM of the offshore wind farms are devised as follows:

(1) *Manpower* cost C_i^M: the *direct maintenance* cost for technical and administrative labour, and the *indirect maintenance* cost for staff welfare expressed as

$$C_i^M = C^{M^V} M_i^V + C^{M^H} M_i^H + C^{M^L} M_i^L, \tag{9}$$

where manpower cost for employees working on vessels, helicopters and land are calculated.

(2) *Equipment* cost C_i^{EQ}: the *direct maintenance* cost for purchasing spare parts and equipment, as well as the *indirect maintenance* cost for the storage and test.

(3) *Infrastructure* cost C_i^I: the *start-up* cost of infrastructures such as ports, docks, and helipads, and the *indirect maintenance* cost of operating and maintaining.

(4) *Environmental monitoring* cost C_i^{EM}: the *indirect maintenance* cost of dynamically monitoring the marine environment suitability.

(5) *Transportation* cost C_i^T: the *fixed* cost for employing and maintaining vessels and helicopters, and the *variable* cost for shipments, i.e., the fuel cost and berthing cost at the turbine is

$$C_i^T = (C^{F^V} V_i + C^{F^H} H_i)/LP_i + (C_i^{S^V} V_i + C_i^{S^H} H_i). \tag{10}$$

(6) *Adjustment* cost C_i^A: the *opportunity* cost for modifying the maintenance schedule.

(7) *Customer relationship management* cost C_i^{CRM}: the *opportunity* cost for maintaining customer relationship.

Thus, these 7 elements constitute the fuzzy maintenance cost $\tilde{C}_{i,t}$ of TR_i in PR_t as

$$\tilde{C}_{i,t} = C_i^M e^{\tilde{\lambda}_{i,t}^M} + C_i^{EQ} e^{\tilde{\lambda}_{i,t}^{EQ}} + C_i^I e^{\tilde{\lambda}_{i,t}^I} + C_i^{EM} e^{\tilde{\lambda}_{i,t}^{EM}} + C_i^T e^{\tilde{\lambda}_{i,t}^T} + C_i^A e^{\tilde{\lambda}_{i,t}^A} + C_i^{CRM} e^{\tilde{\lambda}_{i,t}^{CRM}}, \tag{11}$$

where each term has a deterministic cost C_i multiplying a time-dependent fuzzy cost weight coefficient $e^{\tilde{\lambda}_{i,t}}$. The fuzzy cost weight is a natural exponential function with a fuzzy exponent $\tilde{\lambda}_{i,t}$ no less than 0. It means that the actual maintenance cost can be represented better and more reasonably by considering it as fuzzy, instead of either deterministic or stochastic as the imprecision and uncertainty of cost data pose a challenge while estimating the data based on an uncertain ocean environment (Baños et al. 2011; Coşgun et al. 2014). The fuzzy cost weight synthesizes the direct effects of the marine environment, e.g., waves and storms on the accessibility and operability of the maintenance works, as well as its indirect effects on the turbines and system deterioration caused by marine corrosion, e.g., salt, microbes, and ocean currents. All these effects increase the difficulty of maintenance and contribute to the cost accumulation and over-runs of each element uncertainly. For this reason, we set the fuzzy exponent as a triangular fuzzy variable to help depict the cost trend and make the cost criterion realistic.

Hence, the maintenance cost minimization objective function can be presented as,

$$\min_{\boldsymbol{X}} \sum_{t=1}^{n} \sum_{i=1}^{m} \tilde{C}_{i,t}\, x_{i,t} = \min_{\boldsymbol{X}} \sum_{t=1}^{n} \sum_{i=1}^{m} (C_i^M e^{\tilde{\lambda}_{i,t}^M} + C_i^{EQ} e^{\tilde{\lambda}_{i,t}^{EQ}} + C_i^I e^{\tilde{\lambda}_{i,t}^I} + C_i^{EM} e^{\tilde{\lambda}_{i,t}^{EM}} + C_i^T e^{\tilde{\lambda}_{i,t}^T} + C_i^A e^{\tilde{\lambda}_{i,t}^A} + C_i^{CRM} e^{\tilde{\lambda}_{i,t}^{CRM}})\, x_{i,t}, \tag{12}$$

where the manpower cost $C_{i,t}^M$ and the transportation cost $C_{i,t}^T$ are detailed by their definitions, respectively (see Eqs. (9) and (10)).

3.4. Constraints

We refer to the 13 sets of constraints especially applicable to the offshore wind farm environment designed by Zhong et al. (2018), where the supply and demand constraints are modified as fuzzy constraints in this paper:

(1) *Fuzzy supply and demand* constraints: the electric power virtually generated has taken out the maintenance downtime loss, and should be able to cover the customer demand entirely. So, the fuzzy supply and demand constraints guarantee that power shortages never occur in any period,

$$\sum\nolimits_{i=1}^{m} \tilde{p}_{i,t}(1 - x_{i,t}) - \tilde{d}_t \geq 0, \quad t = 1, 2, \dots, n, \tag{13}$$

where $\tilde{p}_{i,t}$ is defined in Eq. (5). These constraints restrict $\tilde{e}_t$ to be non-negative.

(2) *Maintenance necessity* constraints: each turbine is maintained only once in the time horizon.

(3) *Maintenance continuity* constraints: maintenance work continues to completion.

(4) *Duration* constraints: the maintenance lasts for a fixed period of time.

(5) *Period* constraints: limited number of turbines can be maintained in each period.

(6) *Priority* constraints: maintenance of some turbines needs to be finished before others.

(7) *Deadline* constraints: there are deadlines for maintenance work.

(8) *Weather* constraints: some periods are not allowed for maintenance due to severe weather.

(9) *Manpower* constraints: crew members for maintenance should be enough.

(10) *Vehicle* constraints: the number of vehicles for maintenance should be enough.

(11) *GHG* constraints: total GHG emission should meet the industrial standard.

(12) *Marine ecosystem* constraints: the number of navigating vessels is restricted.

(13) *Bird population* constraints: the number of navigating helicopters is restricted.

3.5. Fuzzy multi-objective chance-constrained programming model

Combining the two objective functions and 13 sets of constraints, a fuzzy MONLP model for our PM scheduling problem of the offshore wind farms in a fuzzy environment is as follows[2],

$$\begin{cases} \max\limits_{\boldsymbol{X}} \sum\limits_{t=1}^{n} \frac{1}{n} \left[\frac{\sum_{i=1}^{m} \tilde{p}_{i,t}(1 - x_{i,t}) - \tilde{d}_t}{\sum_{i=1}^{m} \tilde{p}_{i,t} - \tilde{d}_t} \right]^{s_t} \\ \min\limits_{\boldsymbol{X}} \sum\limits_{t=1}^{n} \sum\limits_{i=1}^{m} \big(C_i^M e^{\tilde{\lambda}_{i,t}^M} + C_i^{EQ} e^{\tilde{\lambda}_{i,t}^{EQ}} + C_i^I e^{\tilde{\lambda}_{i,t}^I} + C_i^{EM} e^{\tilde{\lambda}_{i,t}^{EM}} \\ \qquad\qquad + C_i^T e^{\tilde{\lambda}_{i,t}^T} + C_i^A e^{\tilde{\lambda}_{i,t}^A} + C_i^{CRM} e^{\tilde{\lambda}_{i,t}^{CRM}} \big) \, x_{i,t} \end{cases} \tag{14a}$$

[2]Each constraint in Model (14b) has a label at the end, which maps to the constraint set label in Section3.4.

s.t.

$$
\begin{aligned}
&\textstyle\sum_{i=1}^{m} \tilde{p}_{i,t}(1-x_{i,t}) - \tilde{d}_t \geq 0, \quad t=1,2,\ldots,n \quad \textbf{(1)}\\
&\textstyle\sum_{t=1}^{n} b_{i,t} = 1, \quad i=1,2,\ldots,m \quad \textbf{(2)}\\
&x_{i,t} \geq b_{i,t}, \quad i=1,2,\ldots,m,\ t=1,2,\ldots,n \quad \textbf{(3)}\\
&x_{i,t} - x_{i,t-1} \leq b_{i,t}, \quad i=1,2,\ldots,m,\ t=1,2,\ldots,n \quad \textbf{(3)}\\
&x_{i,t} + x_{i,t-1} + b_{i,t} < 3, \quad i=1,2,\ldots,m,\ t=1,2,\ldots,n \quad \textbf{(3)}\\
&\textstyle\sum_{t=1}^{n} x_{i,t} = LP_i, \quad i=1,2,\ldots,m \quad \textbf{(4)}\\
&\textstyle\sum_{i=1}^{m} x_{i,t} \leq LT_t, \quad t=1,2,\ldots,n \quad \textbf{(5)}\\
&\textstyle\sum_{k=1}^{t} b_{i,k} - b_{j,t} \geq 0, \quad i=1,2,\ldots,m,\ j\neq i,\ t=1,2,\ldots,n \quad \textbf{(6)}\\
&x_{i,t} + x_{j,t} \leq 1, \quad i=1,2,\ldots,m,\ j\neq i,\ t=1,2,\ldots,n \quad \textbf{(6)}\\
&\textstyle\sum_{t=1}^{L_i-LP_i+1} b_{i,t} = 1, \quad i=1,2,\cdots,m \quad \textbf{(7)}\\
&\textstyle\sum_{t\in U} x_{i,t} = 0, \quad i=1,2,\ldots,m \quad \textbf{(8)}\\
&\textstyle\sum_{i=1}^{m} ({M_i}^V + {M_i}^H + {M_i}^L)\, x_{i,t} \leq AM_t, \quad t=1,2,\ldots,n \quad \textbf{(9)}\\
&\textstyle\sum_{i=1}^{m} V_i x_{i,t} \leq AV_t, \quad t=1,2,\ldots,n \quad \textbf{(10)}\\
&\textstyle\sum_{i=1}^{m} H_i x_{i,t} \leq AH_t, \quad t=1,2,\ldots,n \quad \textbf{(10)}\\
&\textstyle\sum_{i=1}^{m} 2z_i b_{i,t}[q^V(\varpi M_i^V + EQ_i^V) + q^H(\varpi M_i^H + EQ_i^H)] \leq GHG, \quad t=1,2,\ldots,n \quad \textbf{(11)}\\
&\textstyle\sum_{i=1}^{m} V_i(b_{i,t} + b_{i,t-LP_i+1}) \leq LV_t, \quad t=1,2,\ldots,n \quad \textbf{(12)}\\
&\textstyle\sum_{i=1}^{m} H_i(b_{i,t} + b_{i,t-LP_i+1}) \leq LH_t, \quad t=1,2,\ldots,n \quad \textbf{(13)}\\
&x_{i,t} = 1 \text{ if } \mathrm{TR}_i \text{ is in maintenance in } \mathrm{PR}_t,\ = 0 \text{ otherwise},\\
&b_{i,t} = 1 \text{ if the maintenance of } \mathrm{TR}_i \text{ begins at } \mathrm{PR}_t,\ = 0 \text{ otherwise},
\end{aligned}
\tag{14b}
$$

with $\tilde{p}_{i,t}$ defined in Eq. (5), and $x_{i,t}$ and $b_{i,t}$ both decision variables. The optimization target is to obtain a turbine maintenance schedule such that reliability is maximized and cost is minimized simultaneously with all constraints satisfied.

From Model (14a, b), the two objective functions and the first set of constraints are fuzzy quantities. In order to have an unambiguous explanation of the model, the expected values of fuzzy objectives are used to obtain decisions with optimal expected returns, as well as to provide confidence levels α_t within which the fuzzy constraints hold. Therefore, Model (14a, b) can be rewritten as an FCCP by replacing the two objective functions and the first set of constraints as,

$$\begin{cases} \max\limits_{\boldsymbol{X}} \mathbb{E}\left\{ \sum\limits_{t=1}^{n} \dfrac{1}{n} \left[\dfrac{\sum_{i=1}^{m} \tilde{p}_{i,t}(1-x_{i,t}) - \tilde{d}_t}{\sum_{i=1}^{m} \tilde{p}_{i,t} - \tilde{d}_t} \right]^{s_t} \right\} \\ \min\limits_{\boldsymbol{X}} \mathbb{E}\Bigg[\sum\limits_{t=1}^{n} \sum\limits_{i=1}^{m} \big(C_i^{M} e^{\tilde{\lambda}_{i,t}^{M}} + C_i^{EQ} e^{\tilde{\lambda}_{i,t}^{EQ}} + C_i^{I} e^{\tilde{\lambda}_{i,t}^{I}} + C_i^{EM} e^{\tilde{\lambda}_{i,t}^{EM}} \\ \qquad + C_i^{T} e^{\tilde{\lambda}_{i,t}^{T}} + C_i^{A} e^{\tilde{\lambda}_{i,t}^{A}} + C_i^{CRM} e^{\tilde{\lambda}_{i,t}^{CRM}} \big)\, x_{i,t} \Bigg] \end{cases} \tag{15a}$$

$$\begin{aligned} &\text{s.t.} \\ &\quad \mathrm{Cr}\left\{ \tilde{d}_t - \textstyle\sum_{i=1}^{m} \tilde{p}_{i,t}(1-x_{i,t}) \le 0 \right\} \ge \alpha_t, \quad t = 1, 2, \ldots, n \\ &\quad \text{constraints } \textbf{(2)-(13)}, \\ &\quad x_{i,t} = 1 \text{ if } \mathrm{TR}_i \text{ is in maintenance in } \mathrm{PR}_t, \ = 0 \text{ otherwise}, \\ &\quad b_{i,t} = 1 \text{ if the maintenance of } \mathrm{TR}_i \text{ begins at } \mathrm{PR}_t, \ = 0 \text{ otherwise}, \end{aligned} \tag{15b}$$

with $\tilde{p}_{i,t}$ defined in Eq. (5). For simplicity, the 12 sets of constraints shown in Model (14a, b) are described as constraints **(2)-(13)** hereafter.

4. 2-phase solution framework

A 2-phase solution framework integrating the operational law for fuzzy arithmetic and NSGA-II for multi-objective programming is developed to solve the fuzzy multi-objective non-linear chance-constrained programming Model (15a, b) proposed for the PM scheduling problem of offshore wind farms in a fuzzy environment.

4.1. Phase I: Operational law

Phase I employs the operational law which applies accurate fuzzy arithmetic instead of fuzzy approximations or simulation to simplify the FCCP in Model (15a, b), converting it to the equivalent deterministic programming which has ready solution methods. Subsequently, the treated model proceeds to Phase II.

(1) In the FCCP Model (15a), the first expected reliability objective function can be expanded referring to Eq. (A.10) owing to the independence of the fuzzy variables. In each expected term, $\tilde{r}_t$ is strictly decreasing w.r.t. $\tilde{d}_t$, and its monotonicity concerning $\tilde{p}_{i,t}$, $i = 1, 2, \ldots, m$, is determined by the values of the corresponding decision variables $x_{i,t}$, $i = 1, 2, \ldots, m$. Clearly, $\tilde{r}_t$ is strictly increasing w.r.t. $\tilde{p}_{i,t}$ when $x_{i,t} = 0$, and strictly decreasing when $x_{i,t} = 1$. In addition, all $\tilde{d}_t$ and

$\tilde{p}_{i,t}$ in this objective are triangular fuzzy variables which are special cases of the regular LR fuzzy numbers. Thus, applying Eq. (A.12),

$$\mathbb{E}\left\{\sum_{t=1}^{n}\frac{1}{n}\left[\frac{\sum_{i=1}^{m}\tilde{p}_{i,t}(1-x_{i,t})-\tilde{d}_t}{\sum_{i=1}^{m}\tilde{p}_{i,t}-\tilde{d}_t}\right]^{s_t}\right\}=$$

$$\frac{1}{n}\sum_{t=1}^{n}\int_0^1\left\{\frac{\sum\limits_{i=1}^{m}\left[\Upsilon_{i,t}^{-1}(\alpha)(1-x_{i,t})+\Upsilon_{i,t}^{-1}(1-\alpha)x_{i,t}\right](1-x_{i,t})-\Psi_t^{-1}(1-\alpha)}{\sum\limits_{i=1}^{m}\left[\Upsilon_{i,t}^{-1}(\alpha)(1-x_{i,t})+\Upsilon_{i,t}^{-1}(1-\alpha)x_{i,t}\right]-\Psi_t^{-1}(1-\alpha)}\right\}^{s_t}\mathrm{d}\alpha, \tag{16}$$

where Ψ_t^{-1} is the inverse credibility distribution of $\tilde{d}_t$ for $t=1,2,\ldots,n$, and $\Upsilon_{i,t}^{-1}$ is the inverse credibility distribution of $\tilde{p}_{i,t}$ for $i=1,2,\ldots,m$, $t=1,2,\ldots,n$. From Eq. (5), $\tilde{p}_{i,t}$ is a piecewise function evaluated at certain expected values of the triangular fuzzy wind speed $\tilde{v}_{i,t}$, and is strictly increasing w.r.t. $\tilde{v}_{i,t}$, so the way to judge the monotonicity of $\tilde{r}_t$ regarding $\tilde{v}_{i,t}$ is the same with that of $\tilde{p}_{i,t}$. Thus, we can substitute the inverse credibility distribution of $\tilde{v}_{i,t}$ indirectly through Eq. (5) into the crisp reliability objective function in Eq. (16).

(2) The second expected cost objective function in the FCCP Model (15a) can also be expanded to the sum of expected values based on Eq. (A.10) as all fuzzy exponents $\tilde{\lambda}_{i,t}^{M}$, $\tilde{\lambda}_{i,t}^{EQ}$, $\tilde{\lambda}_{i,t}^{I}$, $\tilde{\lambda}_{i,t}^{EM}$, $\tilde{\lambda}_{i,t}^{T}$, $\tilde{\lambda}_{i,t}^{A}$, $\tilde{\lambda}_{i,t}^{CRM}$, $i=1,2,\ldots,m$, $t=1,2,\ldots,n$, are independent triangular fuzzy variables. Since each expanded term is strictly increasing w.r.t. the inclusive fuzzy exponents, in accordance with Eq. (A.12),

$$\mathbb{E}\Big[\sum_{t=1}^{n}\sum_{i=1}^{m}\big(C_i^{M}e^{\tilde{\lambda}_{i,t}^{M}}+C_i^{EQ}e^{\tilde{\lambda}_{i,t}^{EQ}}+C_i^{I}e^{\tilde{\lambda}_{i,t}^{I}}+C_i^{EM}e^{\tilde{\lambda}_{i,t}^{EM}}+C_i^{T}e^{\tilde{\lambda}_{i,t}^{T}}+C_i^{A}e^{\tilde{\lambda}_{i,t}^{A}}+C_i^{CRM}e^{\tilde{\lambda}_{i,t}^{CRM}}\big)\,x_{i,t}\Big]$$

$$=\sum_{t=1}^{n}\sum_{i=1}^{m}\int_0^1\big(C_i^{M}e^{\Phi_{i,t}^{M\,-1}(\alpha)}+C_i^{EQ}e^{\Phi_{i,t}^{EQ\,-1}(\alpha)}+C_i^{I}e^{\Phi_{i,t}^{I\,-1}(\alpha)}+$$
$$C_i^{EM}e^{\Phi_{i,t}^{EM\,-1}(\alpha)}+C_i^{T}e^{\Phi_{i,t}^{T\,-1}(\alpha)}+C_i^{A}e^{\Phi_{i,t}^{A\,-1}(\alpha)}+C_i^{CRM}e^{\Phi_{i,t}^{CRM\,-1}(\alpha)}\big)\,x_{i,t}\,\mathrm{d}\alpha$$

$$=\sum_{t=1}^{n}\sum_{i=1}^{m}x_{i,t}\big(C_i^{M}\int_0^1 e^{\Phi_{i,t}^{M\,-1}(\alpha)}\mathrm{d}\alpha+C_i^{EQ}\int_0^1 e^{\Phi_{i,t}^{EQ\,-1}(\alpha)}\mathrm{d}\alpha+C_i^{I}\int_0^1 e^{\Phi_{i,t}^{I\,-1}(\alpha)}\mathrm{d}\alpha+$$
$$C_i^{EM}\int_0^1 e^{\Phi_{i,t}^{EM\,-1}(\alpha)}\mathrm{d}\alpha+C_i^{T}\int_0^1 e^{\Phi_{i,t}^{T\,-1}(\alpha)}\mathrm{d}\alpha+C_i^{A}\int_0^1 e^{\Phi_{i,t}^{A\,-1}(\alpha)}\mathrm{d}\alpha+C_i^{CRM}\int_0^1 e^{\Phi_{i,t}^{CRM\,-1}(\alpha)}\mathrm{d}\alpha\big), \tag{17}$$

where $\Phi_{i,t}^{M\,-1}$, $\Phi_{i,t}^{EQ\,-1}$, $\Phi_{i,t}^{I\,-1}$, $\Phi_{i,t}^{EM\,-1}$, $\Phi_{i,t}^{T\,-1}$, $\Phi_{i,t}^{A\,-1}$, $\Phi_{i,t}^{CRM\,-1}$, $i=1,2,\ldots,m$, $t=1,2,\ldots,n$, are inverse credibility distributions of all the fuzzy exponents, respectively.

(3) With respect to the first set of chance constraints in Eq. (15b) of the FCCP model, the constraint function for PR_t is strictly increasing w.r.t. $\tilde{d}_t$, and strictly decreasing w.r.t. $\tilde{p}_{i,t}$, $i = 1, 2, \ldots, m$. As all of the above fuzzy variables are independent triangular, in terms of Eq. (A.14), the chance constraints hold iff

$$\Psi_t^{-1}(\alpha_t) - \sum\nolimits_{i=1}^{m} \Upsilon_{i,t}^{-1}(1-\alpha_t)(1-x_{i,t}) \leq 0, \quad t = 1, 2, \ldots, n, \tag{18}$$

in which for a certain t, Ψ_t^{-1} are inverse credibility distributions of $\tilde{d}_t$, and $\Upsilon_{i,t}^{-1}$ are the inverse credibility distributions of $\tilde{p}_{i,t}$ for $i = 1, 2, \cdots, m$ as specified in the reliability objective in Eq. (16). Also, $\Upsilon_{i,t}^{-1}$ needs to be substituted by the inverse credibility distribution of $\tilde{v}_{i,t}$ by virtue of Eq. (5).

Therefore, integrating the above three conversions in the same way as Model (A.15), the equivalent deterministic model of the FCCP Model (15a, b) is shown as,

$$\begin{cases} \max\limits_{\boldsymbol{X}} \dfrac{1}{n} \sum\limits_{t=1}^{n} \displaystyle\int_0^1 \left\{ \frac{\sum\limits_{i=1}^{m} \left[\Upsilon_{i,t}^{-1}(\alpha)(1-x_{i,t}) + \Upsilon_{i,t}^{-1}(1-\alpha)x_{i,t} \right](1-x_{i,t}) - \Psi_t^{-1}(1-\alpha)}{\sum\limits_{i=1}^{m} \left[\Upsilon_{i,t}^{-1}(\alpha)(1-x_{i,t}) + \Upsilon_{i,t}^{-1}(1-\alpha)x_{i,t} \right] - \Psi_t^{-1}(1-\alpha)} \right\}^{s_t} \mathrm{d}\alpha \\ \min\limits_{\boldsymbol{X}} \sum\limits_{t=1}^{n} \sum\limits_{i=1}^{m} x_{i,t} \Big(C_i^{M} \displaystyle\int_0^1 e^{\Phi_{i,t}^{M\,-1}(\alpha)} \mathrm{d}\alpha + C_i^{EQ} \int_0^1 e^{\Phi_{i,t}^{EQ\,-1}(\alpha)} \mathrm{d}\alpha + C_i^{I} \int_0^1 e^{\Phi_{i,t}^{I\,-1}(\alpha)} \mathrm{d}\alpha + \\ \qquad C_i^{EM} \displaystyle\int_0^1 e^{\Phi_{i,t}^{EM\,-1}(\alpha)} \mathrm{d}\alpha + C_i^{T} \int_0^1 e^{\Phi_{i,t}^{T\,-1}(\alpha)} \mathrm{d}\alpha + C_i^{A} \int_0^1 e^{\Phi_{i,t}^{A\,-1}(\alpha)} \mathrm{d}\alpha + \\ \qquad C_i^{CRM} \displaystyle\int_0^1 e^{\Phi_{i,t}^{CRM\,-1}(\alpha)} \mathrm{d}\alpha \Big) \end{cases} \tag{19a}$$

s.t.

$$\begin{aligned} & \Psi_t^{-1}(\alpha_t) - \textstyle\sum_{i=1}^{m} \Upsilon_{i,t}^{-1}(1-\alpha_t)(1-x_{i,t}) \leq 0, \quad t = 1, 2, \ldots, n \\ & \text{constraints } \textbf{(2)-(13)}, \\ & x_{i,t} = 1 \text{ if } \mathrm{TR}_i \text{ is in maintenance in } \mathrm{PR}_t, \ = 0 \text{ otherwise}, \\ & b_{i,t} = 1 \text{ if the maintenance of } \mathrm{TR}_i \text{ begins at } \mathrm{PR}_t, \ = 0 \text{ otherwise}, \end{aligned} \tag{19b}$$

in which $\Upsilon_{i,t}^{-1}$ needs to be substituted by the inverse credibility distribution of $\tilde{v}_{i,t}$ according to Eq. (5). The equivalent crisp programming Model (19a, b) can replace the FCCP Model (15a, b), and we proceed to the next phase to develop appropriate algorithms.

4.2. Phase II: NSGA-II

Phase II designs a nondominated sorting genetic algorithm II (NSGA-II) based algorithm to deal with the remaining deterministic MONLP Model (19a, b) to obtain a set of Pareto-optimal solutions.

In NSGA-II, the fast nondominated sorting procedure, the fast crowding distance estimation procedure, and the simple crowded-comparison operator negate significantly any weakness of the former NSGA. As none of the Pareto-optimal solutions are better than any solution, each of them is acceptable. They can provide various trade-off solutions for decision-makers to determine a satisficing schedule for the PM of an offshore wind project. The entire procedure of the NSGA-II for solving the crisp MONLP Model (19a, b) is presented in Algorithm 1.

Algorithm 1 NSGA-II for PM scheduling model of offshore wind farms in a fuzzy environment

1: Set t=1;
2: Initialize parent population P_0 and set it as P_t with *pop_size* feasible solutions after checking all constraints.
3: Calculate values of objective functions Eqs. (16) and (17) in Model (19a) for all solutions in P_t.
4: Rank solutions in P_t based on the fast nondominated sorting approach. So each solution i is assigned with a nondomination rank i_{rank}.
5: Calculate the crowding distance $i_{distance}$ of each solution i in P_t based on the density estimation metric.
6: Select *pop_size* solutions by the binary tournament selection utilizing the crowded comparison operator which is based on the nondomination rank i_{rank} and the crowding distance $i_{distance}$. The selected solutions are used to create an offspring population.
7: Update solutions by crossover and mutation operations. The feasibility of offspring population Q_t should be checked by constraints **(1)-(13)** in Model (19b).
8: Execute the elitist strategy containing the combination and comparison of P_t and Q_t. $t \leftarrow t+1$, and the new P_t with *pop_size* solutions is output for the next iteration.
9: Repeat Steps 6-8 for a given number of iterations.
10: Collect Pareto-optimal solutions to support the decision-making.

5. Numerical example

We design a numerical example to validate the effectiveness and performance of the proposed fuzzy multi-objective non-linear chance-constrained programming Model (15a, b) for the PM scheduling of offshore wind farms in the fuzzy environment and the 2-phase solution framework. The background and parameters of the illustrative case and algorithm are given in the supplementary material.

5.1. Effect of decision-maker attitudes

As there are four types of decision-maker attitudes towards the offshore wind project over the time horizon, i.e., fully rational, optimism biased, wait-and-see, and pessimism biased preferences, we discuss their different effects on the final solution sets in this section.

First, we use four sets of 52 attainment exponents to present the four attitudes by allocating them with positive, neutral or negative effects in Table 2. As to the fully rational attitude (columns 2 and 7), we select $s_1, s_2, \ldots, s_{18}$ randomly from $[0, 1)$, make $s_{19}, s_{20}, \ldots, s_{34}$ all equal to 1, and choose $s_{35}, s_{36}, \ldots, s_{52}$ randomly from $(1, 50)$, which can be approximately equivalent to the interval $(1, +\infty)$. For the optimism biased attitude (columns 3 and 8), $s_1, s_2, \ldots, s_{52}$ are entirely from $[0, 1)$. For the wait-and-see attitude (columns 4 and 9), all s_t equal to 1. For the pessimism biased attitude (columns 5 and 11), s_t are selected from $(1, 50)$.

Then, four crisp multi-objective programming models (19a, b) with different decision-maker attitudes are implemented for 5,000 iterations, respectively, and the final solution sets are displayed in Fig. 2[3] by four point types and in Table 3. It can be seen that the results on the basis of the fully rational attitude (blue asterisks in Fig. 2 and row 2 in Table 3) have the lowest maintenance cost (€21.8696∼23.5552m) and good system reliability (96.6390∼98.5896%) attainments, as well as the best spread of Pareto-optimal solutions which does not contain big gaps among solutions as the other three solution sets do. Hence, a rational attitude is more appropriate for decision-makers to hold as it contributes to more reasonable and high-performance outputs. They can better support the subsequent decision-making of selecting one or several satisfying solutions from the solution set as the schedules to execute maintenance jobs. In the following analyses, we will focus on this attitude.

5.2. Decision-making guidance under different strategic preferences

We analyse the Pareto-optimal solutions of the crisp Model (19a, b) to guide the decision-making on the PM scheduling problem of offshore wind farms in the fuzzy environment. The values of s_t are assigned according to the fully rational attitude, i.e., the columns 2 and 7 of Table 2. In Fig. 3, the asterisks represent 100 Pareto-optimal solutions after 5,000 iterations. We

[3]In Fig. 2, one set of points is one solution set, comprising 100 Pareto-optimal solutions representing 100 satisfying maintenance schedules with their cost and reliability goal values indicated in x-axis and y-axis.

Table 2: Assignment of s_t according to decision-maker attitudes

s_t	Rational	Optimism	W&s	Pessimism	s_t	Rational	Optimism	W&s	Pessimism
s_1	0.21	0.58	1	47.50	s_{27}	1	0.03	1	2.06
s_2	0.29	0.12	1	19.21	s_{28}	1	0.24	1	17.95
s_3	0.70	0.41	1	9.78	s_{29}	1	0.97	1	23.91
s_4	0.71	0.67	1	15.47	s_{30}	1	0.15	1	2.22
s_5	0.72	0.68	1	4.85	s_{31}	1	0.84	1	7.84
s_6	0.23	0.01	1	3.44	s_{32}	1	0.48	1	39.87
s_7	0.84	0.81	1	10.17	s_{33}	1	0.07	1	8.92
s_8	0.93	0.70	1	32.29	s_{34}	1	0.40	1	5.05
s_9	0.41	0.17	1	35.85	s_{35}	14.04	0.66	1	40.52
s_{10}	0.69	0.61	1	27.68	s_{36}	40.11	0.78	1	27.84
s_{11}	0.25	0.29	1	38.26	s_{37}	23.70	0.33	1	22.65
s_{12}	0.79	0.37	1	4.26	s_{38}	19.45	0.74	1	28.53
s_{13}	0.96	0.72	1	6.63	s_{39}	49.97	0.44	1	43.74
s_{14}	0.53	0.27	1	11.81	s_{40}	39.96	0.02	1	22.35
s_{15}	0.95	0.11	1	24.01	s_{41}	3.63	0.23	1	27.27
s_{16}	0.01	0.06	1	18.02	s_{42}	45.28	0.86	1	40.59
s_{17}	0.12	0.06	1	18.60	s_{43}	46.61	0.79	1	5.31
s_{18}	0.40	0.04	1	47.53	s_{44}	23.06	0.07	1	7.99
s_{19}	1	0.06	1	16.15	s_{45}	36.72	0.48	1	4.51
s_{20}	1	0.16	1	20.32	s_{46}	28.96	0.91	1	40.40
s_{21}	1	0.78	1	14.56	s_{47}	36.90	0.82	1	9.90
s_{22}	1	0.19	1	40.26	s_{48}	15.47	0.60	1	35.70
s_{23}	1	0.17	1	1.45	s_{49}	9.09	0.48	1	4.38
s_{24}	1	0.44	1	29.57	s_{50}	6.96	0.07	1	35.08
s_{25}	1	0.97	1	10.37	s_{51}	42.39	0.87	1	30.01
s_{26}	1	0.69	1	47.58	s_{52}	21.46	0.56	1	46.84

extract decision instructions under different strategic preferences of an offshore wind project as follows:

(1) If the offshore wind project follows a cost priority strategy, it means that the decision-makers are inclined to optimize the maintenance cost by sacrificing the achievement on reliability. So long as the reliability does not exceed the tolerance which would influence the basic stability,

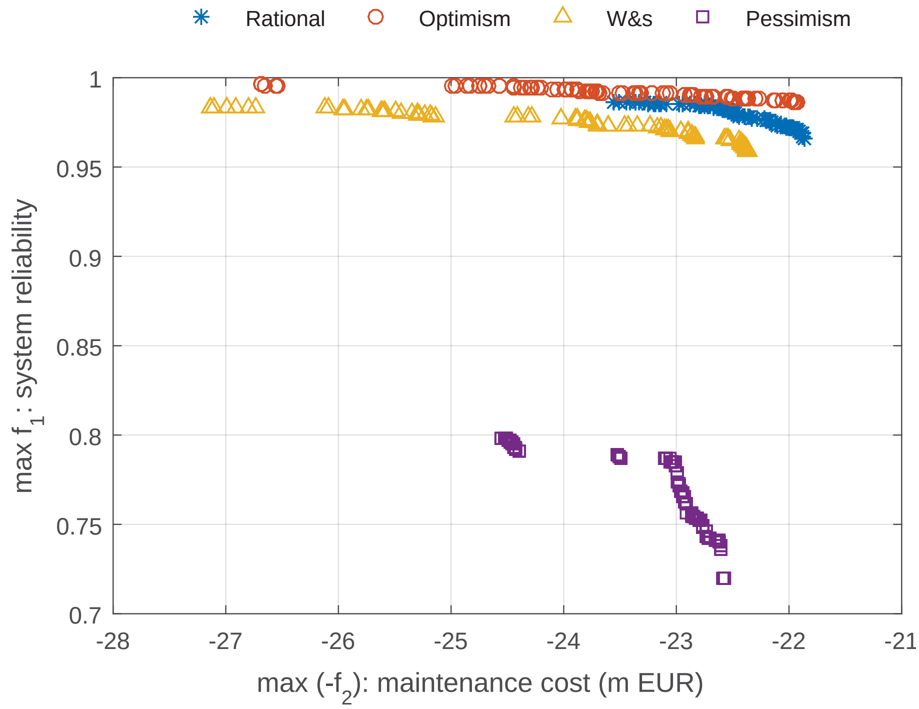


Fig. 2: Effect of decision-maker attitudes on Pareto-optimal solutions

the decision-makers are willing to adopt a lower cost solution albeit with not high but acceptable reliability.

For example, the solution with the lowest cost €21.8696m and the reliability 96.6390% (the asterisk on the bottom right corner in Fig. 3), can be chosen as a maintenance policy of cost priority. The corresponding schedule is displayed in Fig. 4a, in which the colour blocks refer to the periods in maintenance and it summarizes in the last row the amount of turbines in maintenance in each period. The maintenance works are highly assembled (78% workload completed) in the

Table 3: Bounds of the two objectives with different decision-maker attitudes

Attitude	Cost^L(m€)	Cost^U(m€)	Reliability^L(%)	Reliability^U(%)
Rational	21.8696	23.5552	96.6390	98.5896
Optimism	21.9351	26.6912	98.6020	99.5978
Wait-and-see	22.3641	27.1397	95.8669	98.3111
Pessimism	22.5800	24.5500	71.9563	79.8157

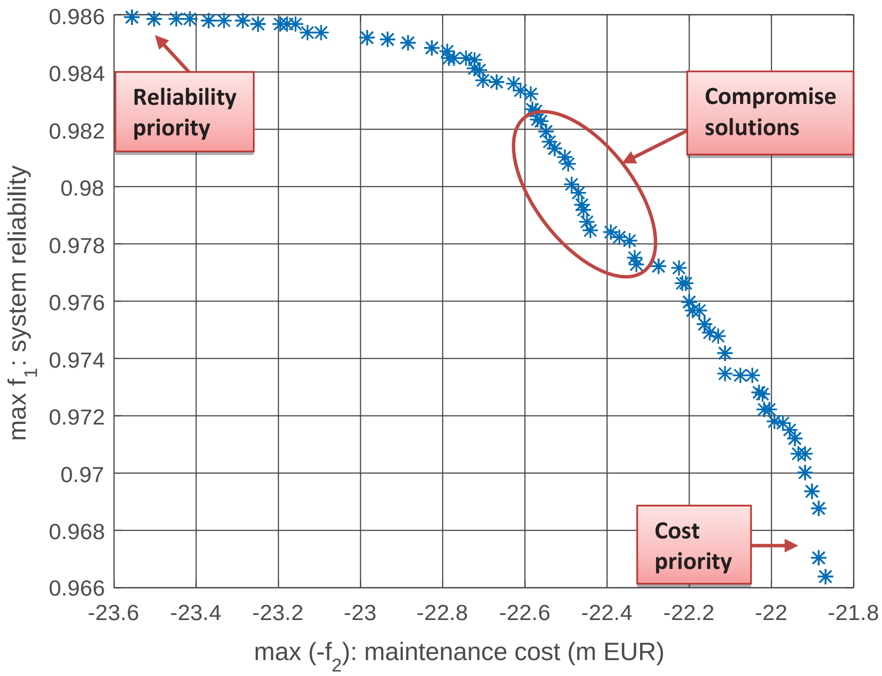


Fig. 3: Pareto-optimal solutions with fully rational attitude

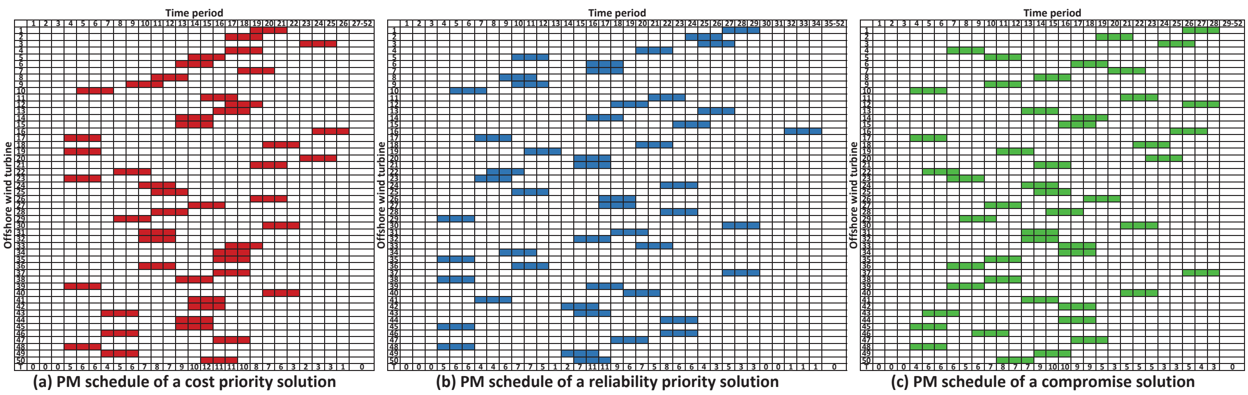
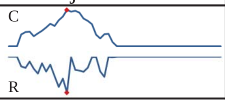
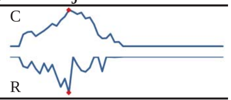
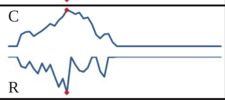
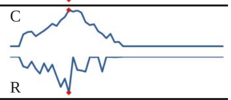
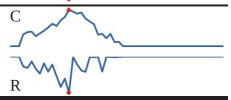
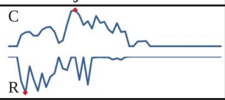
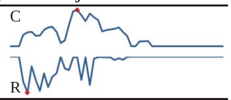
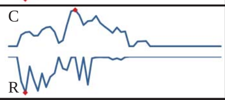
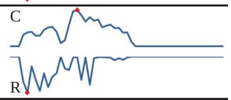
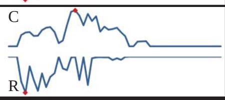
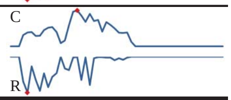


Fig. 4: Maintenance schedule examples in different strategic priorities

(a) Pareto-optimal solutions for cost priority strategy

Solution	Cost (m€)	Reliability (%)	Objective trend	Solution	Cost (m€)	Reliability (%)	Objective trend
1	21.8696	96.6390		4	21.9011	96.9385	
2	21.8843	96.7017		5	21.9184	97.0044	
3	21.8864	96.8758		6	21.9202	97.0667	

(b) Pareto-optimal solutions for reliability priority strategy

Solution	Cost (m€)	Reliability (%)	Objective trend	Solution	Cost (m€)	Reliability (%)	Objective trend
1	23.5552	98.5896		4	23.4153	98.5844	
2	23.5027	98.5869		5	23.3689	98.5802	
3	23.4480	98.5864		6	23.3341	98.5791	

(c) Pareto-optimal solutions for compromise strategy

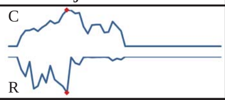
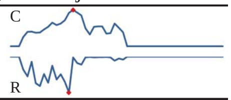
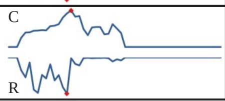
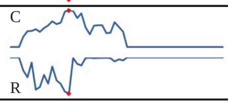
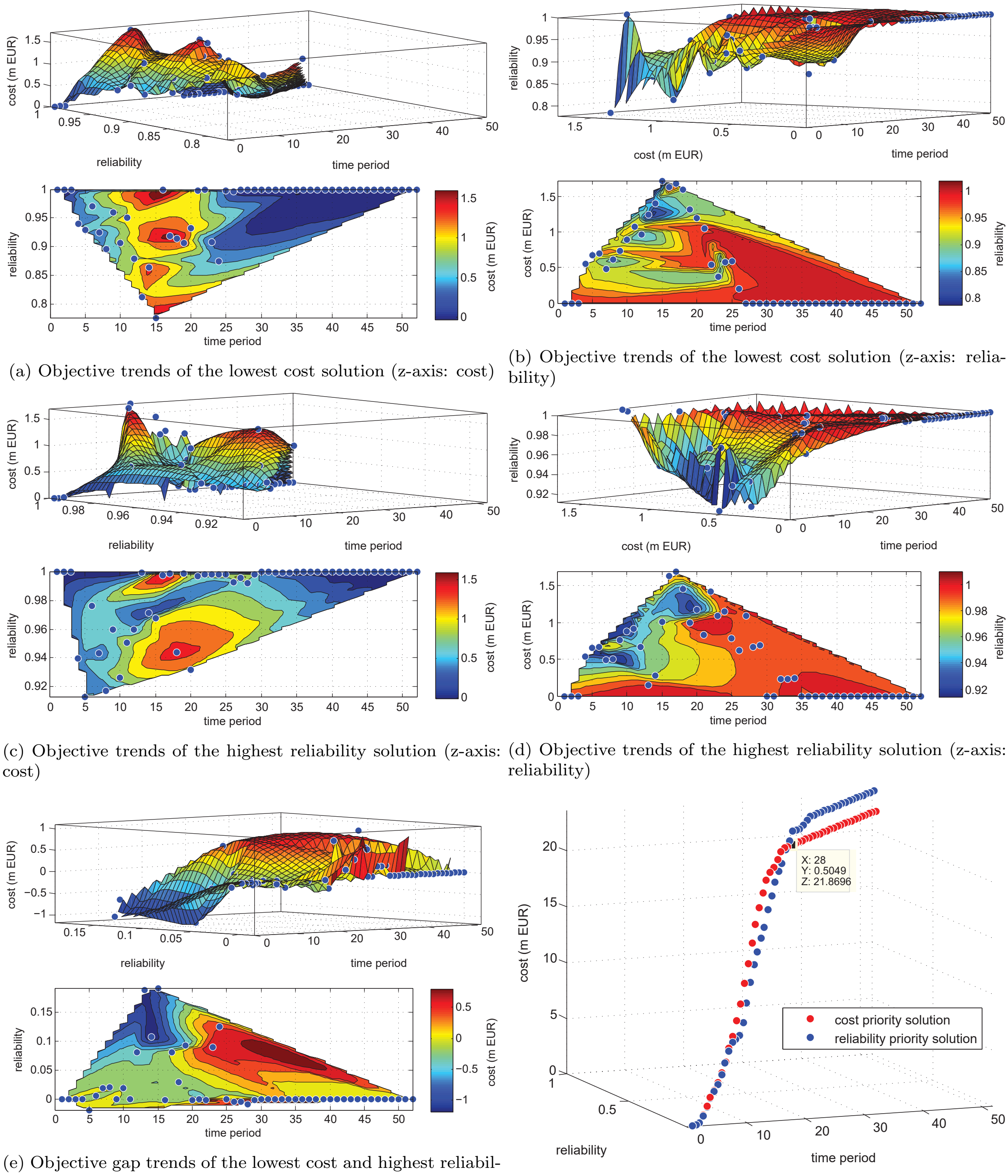
Solution	Cost (m€)	Reliability (%)	Objective trend	Solution	Cost (m€)	Reliability (%)	Objective trend
1	22.4857	98.0061		4	22.5286	98.1316	
2	22.4943	98.0770		5	22.4692	97.9758	
3	22.5035	98.1013		6	22.4627	97.9356	

Fig. 5: Pareto-optimal solution examples in different strategic priorities

first third of the time horizon, especially from PR_{14} to PR_{18}, which is consistent with the principle of the cost saving strategy, implying that maintenance should be done as early as possible to avoid the exponential increase in cost over time. Besides, five other cost priority solutions are given in Fig. 5a, as well as their cost and reliability objective trends over time with the respective extrema shown.

(2) If the offshore wind project implements a reliability priority strategy, i.e., satisfying customer power demand is more important to decision-makers and there is sufficient maintenance budget, the Pareto-optimal solutions in the top left corner of Fig. 3 are the best choices for maintenance



(a) Objective trends of the lowest cost solution (z-axis: cost)

(b) Objective trends of the lowest cost solution (z-axis: reliability)

(c) Objective trends of the highest reliability solution (z-axis: cost)

(d) Objective trends of the highest reliability solution (z-axis: reliability)

(e) Objective gap trends of the lowest cost and highest reliability solutions

(f) Objective cumulation trends of the lowest cost and highest reliability solutions

Fig. 6: Surface fitting and contour for objective (gap and cumulation) trends of different priority solutions

policies. As long as the maintenance cost is not over budget, a higher reliability level can be expected.

The upper bound decision with the highest reliability 98.5896% and the cost €23.5552m can be found in Fig. 5b, as well as five other reliability priority solutions. Since the highest reliability solution is the extreme case among all Pareto-optimal solutions just like the lowest cost solution, we place their objective (gap and cumulation) trends over time in Fig. 6 for comparison.

Fig. 6 shows why the maintenance of the highest reliability solution in Fig. 4b is scheduled less concertedly than that of the lowest cost solution in Fig. 4a (there are turbines in maintenance from PR_4 to PR_{34}). It is to ensure the reliability of wind farm remains high stably (Figs. 6c-6d versus Figs. 6a-6b reveal). The reliability of the highest reliability solution almost always keeps ahead in the time horizon (see Fig. 6e). Also, the highest reliability solution results in lower cost in early periods and higher cost in late periods, finally leading to overtaking in the cumulative cost since PR_{28} (see Fig. 6f). Moreover, early maintenance contributes more to the reliability achievement than mid-stage maintenance. Therefore the number of turbines in maintenance from PR_4 to PR_{18} is (54%) larger than that from PR_{19} to PR_{34}.

(3) If reducing maintenance cost and increasing system reliability are both crucial strategies for the offshore wind project, compromise policies which attempt to satisfy both targets are needed. The compromise solutions are marked by the circle in Fig. 3, and six of them are listed in Fig. 5c. The maintenance schedule of the first solution is indicated in Fig. 4c. It shows that the compromise solutions fall in between the cost priority and reliability priority solutions.

In sum, no matter what strategic preferences decision-makers have for the offshore wind project, Pareto-optimal solutions obtained from the optimization can provide adequate alternative satisfying solutions: maintenance schedules of the cost priority solutions are distributed in early short periods intensively, while those of the reliability priority solutions are arranged in longer periods more dispersedly. In the future, decision-makers can apply our framework to their cases by inputting real data, and choose suitable policies according to our guidance.

The rationality of the approach proposed in this paper to formulate and solve the PM problem provides a novel direction comparing with that of Zhong et al. (2018). As we are not in a position to make numerical comparisons between the results derived here with those of Zhong et al. (2018), therefore we appraise the approaches by evaluating the results regarding the significance levels of their characteristics. Comparing the PM schedule results shown in Fig. 4 with that of Zhong et al. (2018), we can see that in this paper the PM works in the schedules of the lowest cost (Fig. 4a) and the highest reliability solution (Fig. 4b) have distinctly different distribution patterns as summarized above, while in Zhong et al. (2018) we cannot find and extract that the two same objects (Figs. 4a-4b) have much difference in distribution. This comparison supports us to justify that the PM scheduling problem for offshore wind farms being discussed in the fuzzy environment and its associated approach in this paper outperform it being addressed in the deterministic environment in Zhong et al. (2018). Studying the problem in a more practical and reasonable (fuzzy) environment contributes to more realistic and rational results.

5.3. Considering CM cost to get optimal solution and analyse cost performance

In this section, we will give decision-makers a more intuitive idea of what a specific system reliability and its improvement standing for in terms of cost, so as to further support the decision-making of one best choice from the solution set. Hence, we first employ a Risk-Based-Failure Mode and Effect Analysis (RB-FMEA) approach proposed by Kahrobaee and Asgarpoor (2011) to estimate the failure cost (i.e., CM cost) of offshore wind farm. CM cost is the value embodiment of the system failure rate (i.e., 1 − reliability). Then we aggregate the PM and CM costs to form the overall maintenance cost, which comprehensively includes the information of the proactive PM cost to achieve a certain reliability and the reactive CM cost to handle the possible failure occurring in that reliability level. Finally, we can obtain a solution with the lowest overall maintenance cost as the optimal choice. We implement the processes above as follows:

(1) Estimate the CM cost using the RB-FMEA method[4]. Given that CMC: CM cost (failure cost), P_F: failure occurrence chance, P_{UD}: failure undetected chance, C_F: cost consequence of failure, and N_F: failure frequency,

$$CMC = (P_F \cdot P_{UD} \cdot C_F) \cdot N_F, \tag{20}$$

where $P_F = 1 - \mathbb{E}[\tilde{R}], P_{UD} = 0.89, C_F =$ €39.3191m$, N_F = 2.17$/year. It implies that the CM cost CMC maps the reliability $\tilde{R}$. We use the same solution set in Section 5.2 to analyse. The CM

[4]We refer to the RB-FMEA method in Kahrobaee and Asgarpoor (2011). We take some essential result parameters came out of their case study and properly adjust them to be valid for our illustrative case. Here we omit the detailed steps and present directly. Interested readers can find the original parameter table we mainly refer to in the supplementary material.

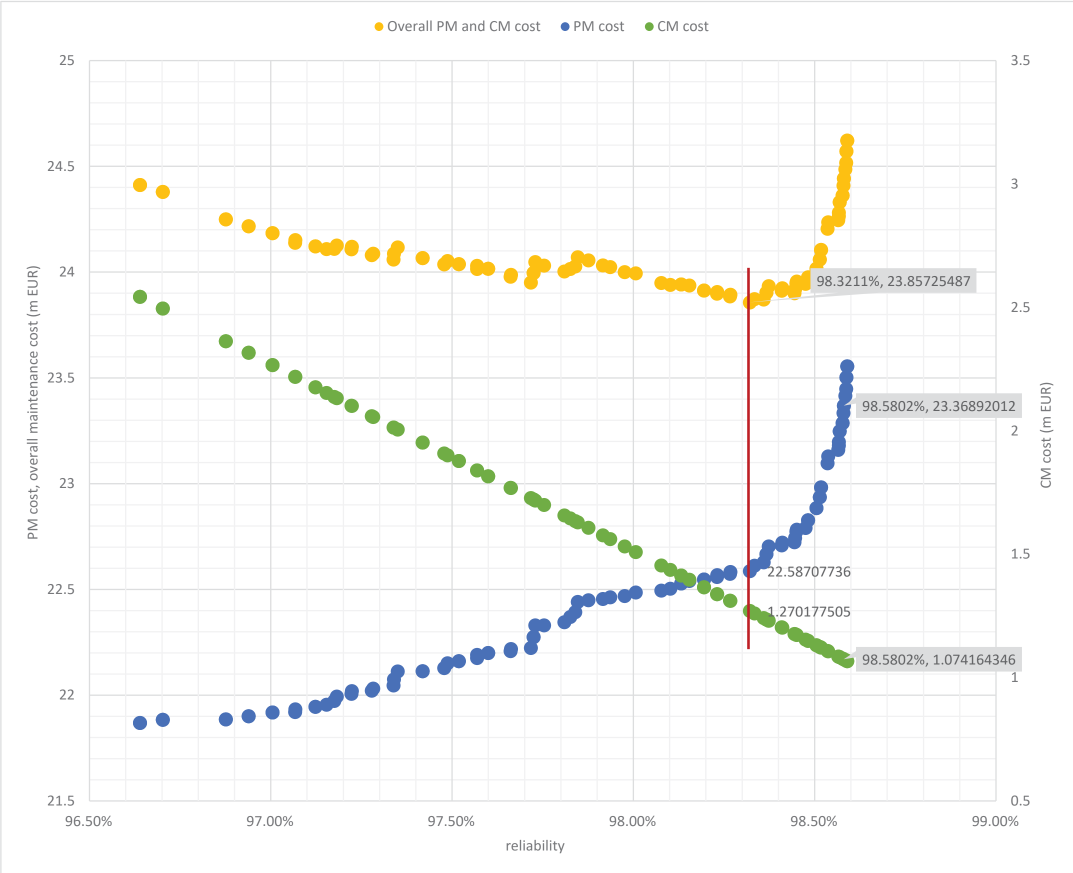


Fig. 7: PM cost, CM cost and overall maintenance cost

costs CMC of the 100 Pareto-optimal solutions are calculated by inputting the reliability values to Eq. (20), and the solution set showing CM cost is denoted by the green dots in Fig. 7. The CM cost decreases as the reliability increases.

(2) Sum up the PM and CM costs as the overall maintenance cost. In Fig. 7, the blue dots refer to the solution set showing PM cost and the yellow dots represent overall maintenance cost. The PM cost, on the contrary, increases as the reliability increases. Thereby, the overall maintenance cost can have a minimum €23.8573m, where the PM cost is €22.5871m and the CM cost is €1.2702m with the reliability at 98.3211%. Decision-makers can see this solution as the final optimal choice.

(3) Cost-benefit analysis between the PM and CM costs. Since the CM cost saving reflects the benefit from reliability improving by investing more PM cost, we observe the ratio change of the CM cost saving to the PM cost investment with the reliability increasing. It can be seen from Fig. 7 that for the solutions with reliability lower than 98.5802%, less PM cost investment can lever

more CM cost saving; while for those with reliability equal or higher than 98.5802%, more PM cost needs to be invested but less CM cost can be saved. Having an understanding of the leverage between the PM and CM costs can also assist decision-makers to weigh the cost performance.

6. Conclusion

This paper, on the basis of Zhong et al. (2018), successfully extends the study of the PM scheduling problem for offshore wind farms in a fuzzy setting by formulating a novel model and designing an associated solving method. Our approach works as a guidance for decision-makers. It is easy to compare, analyze and select the expected results of the model to support PM decisions.

Particularly, this paper contributes in the following five aspects:

(i) We consider the PM scheduling problem for offshore wind farms in the fuzzy setting which is a more realistic thought given the uncertain nature of the marine environment.

(ii) We propose a fuzzy multi-objective non-linear chance-constrained programming model to optimize the reliability and cost objectives simultaneously. The two conflicting objectives are discussed to make a reasonable trade-off. It can be summarized from the experiments that maintenance schedules of the cost priority solutions are distributed in early short periods intensively, while those of the reliability priority solutions are arranged in longer periods more dispersedly.

(iii) We formulate new definitions for the reliability and cost criteria, as well as constraints for the offshore wind energy scenario.

(iv) We develop a 2-phase solution framework integrating the operational law for fuzzy arithmetic and the NSGA-II for multi-objective programming to solve the proposed model.

(v) We bring CM cost (which maps the reliability) into an overall consideration with PM cost to obtain the optimal solution and weigh cost performance for supporting the decision-making. For example, if decision-makers know what a certain reliability value or one percent improvement in reliability mean in cost wise, they can make more sensible decisions of maintenance policies.

In the future, we can refine our maintenance policy design for offshore wind farms continuously by discussing in stochastic or mixed set-ups to find which is more reasonable; further improving the definitions of reliability and cost criteria; combining PM and CM (such as Byon (2013), Duan et al. (2018), Ghamlouch et al. (2017), Luce (1999) and Mo et al. (2018) do) and improving their formulations based on the respective features. Further, we plan to perform the grid optimization of offshore wind energy coordinating with other power systems to cope with the global energy crisis.

Acknowledgements

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Appendix A. Credibility theory and operational law

We introduce the notion of credibility theory and the operational law, which are applied to our problem for refining and solving the fuzzy programming model.

Definition 1. *Let* Θ *be a nonempty set,* $\mathcal{P}(\Theta)$ *the power set of* Θ*, and* Pos *a possibility measure. Then, the tuple* $(\Theta, \mathcal{P}(\Theta), \mathrm{Pos})$ *is called a possibility space.*

Based on possibility space, a fuzzy variable and its membership function can be defined.

Definition 2. *A fuzzy variable is defined as a function from a possibility space* $(\Theta, \mathcal{P}(\Theta), \mathrm{Pos})$ *to the set of real numbers,* $\mathbb{R}$*.*

Definition 3. *Let* ξ *be a fuzzy variable defined on the possibility space* $(\Theta, \mathcal{P}(\Theta), \mathrm{Pos})$*. Then its membership function is derived from the possibility measure given by*

$$\mu(x) = \mathrm{Pos}\{\theta \in \Theta \mid \xi(\theta) = x\}, \quad x \in \mathbb{R}. \tag{A.1}$$

W.r.t. a triangular fuzzy variable, a type of fuzzy variable commonly used in uncertain problems, the fuzzy variable fully determined by the tuple (r_1, r_2, r_3) of crisp numbers with $r_1 < r_2 < r_3$, whose membership function is given by

$$\mu(x) = \begin{cases} \dfrac{x - r_1}{r_2 - r_1}, & \text{if } r_1 \le x \le r_2 \\ \dfrac{x - r_3}{r_2 - r_3}, & \text{if } r_2 \le x \le r_3 \\ 0, & \text{otherwise.} \end{cases} \tag{A.2}$$

Let ξ be a fuzzy variable with membership function μ, and $r \in \mathbb{R}$. Extending to a fuzzy event $\{\xi \leq r\}$, its possibility, necessity, and credibility which measure the chances of the event can be presented as

$$\begin{aligned} \text{Pos}\{\xi \leq r\} &= \sup_{x \leq r} \mu(x), \\ \text{Nec}\{\xi \leq r\} &= 1 - \sup_{x > r} \mu(x), \\ \text{Cr}\{\xi \leq r\} &= \frac{1}{2} \left(\text{Pos}\{\xi \leq r\} + \text{Nec}\{\xi \leq r\} \right) = \frac{1}{2} \left(\sup_{x \leq r} \mu(x) + 1 - \sup_{x > r} \mu(x) \right). \end{aligned} \tag{A.3}$$

The credibility distribution of a fuzzy variable is defined below.

Definition 4. (Liu 2002) *The credibility distribution* $\Phi : \mathbb{R} \to [0, 1]$ *of a fuzzy variable* ξ *is*

$$\Phi(x) = \text{Cr} \left\{ \theta \in \Theta \;\middle|\; \xi(\theta) \leq x \right\}. \tag{A.4}$$

$\Phi(x)$ is the credibility that ξ takes a value no more than x. Liu (2007) proved that the credibility distribution Φ is nondecreasing on $\mathbb{R}$ with $\Phi(-\infty) = 0$ and $\Phi(+\infty) = 1$. Then the inverse function Φ^{-1} is the inverse credibility distribution of ξ. For example, the inverse distribution of a triangular fuzzy number $\xi \sim \mathcal{T}(r_1, r_2, r_3)$ is

$$\Phi^{-1}(\alpha) = \begin{cases} (2r_2 - 2r_1)\alpha + r_1, & \text{if } \alpha < 0.5 \\ (2r_3 - 2r_2)\alpha + 2r_2 - r_3, & \text{if } \alpha \geq 0.5. \end{cases} \tag{A.5}$$

Thereafter, the LR fuzzy number will be applied in the following theorems. It is initialized by Dubois and Prade (1978), which contains the triangular fuzzy number mentioned above as a regular LR fuzzy number acting as a particular case. We now supply the operational law for the regular LR fuzzy numbers.

Theorem 1. (Zhou et al. 2016) *Let* $\xi_1, \xi_2, \ldots, \xi_n$ *be independent regular LR fuzzy numbers with credibility distributions* $\Phi_1, \Phi_2, \ldots, \Phi_n$*, respectively. If the function* $f(x_1, x_2, \ldots, x_n)$ *is strictly increasing w.r.t.* $x_1, x_2, \ldots, x_m$ *and strictly decreasing w.r.t.* $x_{m+1}, x_{m+2}, \ldots, x_n$*, then*

$$\xi = f(\xi_1, \ldots, \xi_m, \xi_{m+1}, \ldots, \xi_n) \tag{A.6}$$

is a regular LR fuzzy number with an inverse credibility distribution

$$\Psi^{-1}(\alpha) = \quad f(\Phi_1^{-1}(\alpha), \ldots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \ldots, \Phi_n^{-1}(1-\alpha)). \tag{A.7}$$

We now provide the definition of the expected value operator of a fuzzy variable, and its properties. While there are many ways to define an expected value operator of fuzzy variables, Liu and Liu (2002) provides the most general definition of the expected value operator of a fuzzy variable (continuous and discrete).

Definition 5. (Liu and Liu 2002) *Let ξ be a fuzzy variable. Then, the expected value of ξ is defined as*

$$\mathbb{E}[\xi] = \int_0^{+\infty} \mathrm{Cr}\{\xi \geq r\}\,\mathrm{d}r - \int_{-\infty}^0 \mathrm{Cr}\{\xi \leq r\}\,\mathrm{d}r \tag{A.8}$$

provided that at least one of the two integrals is finite.

An equivalent form of the expected value for the regular LR fuzzy numbers by virtue of the inverse credibility distribution is proposed as follows.

Theorem 2. (Zhou et al. 2016) *Suppose ξ is a regular LR fuzzy number. If $\mathbb{E}[\xi]$ exists, then*

$$\mathbb{E}[\xi] = \int_0^1 \Phi^{-1}(\alpha)\mathrm{d}\alpha, \tag{A.9}$$

where Φ^{-1} is the inverse credibility distribution of ξ.

Next, the linearity of the expected value operator for fuzzy variables is stated.

Theorem 3. (Liu and Liu 2003) *Let ξ and η be independent fuzzy variables with finite expected values. Then for any a and $b \in \mathbb{R}$, we have*

$$\mathbb{E}[a\xi + b\eta] = a\mathbb{E}[\xi] + b\mathbb{E}[\eta]. \tag{A.10}$$

To formulate the decision systems with fuzzy parameters, we call on the following FCCP model which is a conventional type of fuzzy programming,

$$\begin{cases} \min\limits_{\boldsymbol{x}} \mathbb{E}[f(\boldsymbol{x}, \boldsymbol{\xi})] \\ \text{s.t.} \\ \qquad \mathrm{Cr}\{g_j(\boldsymbol{x}, \boldsymbol{\xi}) \le 0\} \ge \alpha_j, \quad j = 1, 2, \ldots, p. \end{cases} \tag{A.11}$$

Model (A.11) aims to achieve a decision with the minimum expected objective $\mathbb{E}[f(\boldsymbol{x}, \boldsymbol{\xi})]$ subject to a set of chance constraints. If the fuzzy vector $\boldsymbol{\xi}$ consists of regular LR fuzzy numbers, then a crisp equivalent form can be obtained using the following two theorems.

Theorem 4. (Zhou et al. 2016) *Suppose the objective function $f(\boldsymbol{x}, \xi_1, \xi_2, \ldots, \xi_n)$ is strictly increasing w.r.t. $\xi_1, \xi_2, \ldots, \xi_m$ and strictly decreasing w.r.t. $\xi_{m+1}, \xi_{m+2}, \ldots, \xi_n$. If $\xi_1, \xi_2, \ldots, \xi_n$ are independent regular LR fuzzy numbers, then the expected objective function $\mathbb{E}[f(\boldsymbol{x}, \xi_1, \xi_2, \ldots, \xi_n)]$ in Model (A.11) is:*

$$\int_0^1 f(\boldsymbol{x}, \Phi_1^{-1}(\alpha), \ldots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \ldots, \Phi_n^{-1}(1-\alpha))\mathrm{d}\alpha \tag{A.12}$$

where Φ_i^{-1} is the inverse credibility distribution of ξ_i for $i = 1, 2, \ldots, n$.

Theorem 5. (Zhou et al. 2016) *Suppose the constraint function $g_j(\boldsymbol{x}, \xi_1, \xi_2, \ldots, \xi_n)$ is strictly increasing w.r.t. $\xi_1, \xi_2, \ldots, \xi_{k_j}$ and strictly decreasing w.r.t. $\xi_{k_j+1}, \xi_{k_j+2}, \ldots, \xi_n$. If $\xi_1, \xi_2, \ldots, \xi_n$ are independent regular LR fuzzy numbers, then the chance constraint*

$$\mathrm{Cr}\left\{g_j(\boldsymbol{x}, \xi_1, \xi_2, \ldots, \xi_n) \le 0\right\} \ge \alpha \tag{A.13}$$

holds iff

$$g_j(\boldsymbol{x}, \Phi_1^{-1}(\alpha), \ldots, \Phi_{k_j}^{-1}(\alpha), \Phi_{k_j+1}^{-1}(1-\alpha), \ldots, \Phi_n^{-1}(1-\alpha)) \le 0 \tag{A.14}$$

where Φ_i^{-1} is the inverse credibility distribution of ξ_i for $i = 1, 2, \ldots, n$.

As a result, we can convert the fuzzy programming Model (A.11) to the crisp model as,

$$\begin{cases} \min\limits_{\boldsymbol{x}} \int_0^1 f(\boldsymbol{x}, \Phi_1^{-1}(\alpha), \ldots, \Phi_m^{-1}(\alpha), \Phi_{m+1}^{-1}(1-\alpha), \ldots, \Phi_n^{-1}(1-\alpha))\mathrm{d}\alpha \\ \text{s.t.} \\ \qquad g_j(\boldsymbol{x}, \Phi_1^{-1}(\alpha_j), \ldots, \Phi_{k_j}^{-1}(\alpha_j), \Phi_{k_j+1}^{-1}(1-\alpha_j), \ldots, \Phi_n^{-1}(1-\alpha_j)) \leq 0, \quad j = 1, 2, \ldots, p \end{cases} \tag{A.15}$$

where Φ_i^{-1} is the inverse credibility distribution of ξ_i for $i = 1, 2, \ldots, n$. The deterministic Model (A.15) can be solved as a linear or non-linear programming by the traditional methods, for which solutions are readily available.

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