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Project portfolio selection and scheduling optimization based on risk measure: a conditional value at risk approach

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Abstract

Project portfolios are considered "powerful strategic weapons" for implementing corporate strategy. Projects are exposed to different types of risks. Studies on project portfolio optimization have addressed risks either by maximizing the expected net present value or including constraints that place an upper bound on portfolio risk score. However, no study has attempted to minimize the risk of severe low returns by adopting a risk-averse measure. The present study contributes by addressing this research gap and utilizes a risk measure conditional value at risk (CVaR) for decision making. The present paper considers a case study of a dairy firm. It captures financial risk in the form of uncertain project cash inflows and evaluates strategic alignment scores and risk scores for technical, schedule, economic and political, organizational, and statutory clearance risks of projects using an analytical hierarchy process. Further, it formulates three project portfolio selection and scheduling models namely, risk-neutral (max_E), risk-averse (max_CVaR) and combined compromise (max_E_CVaR) models. A comparison of results shows that the max_CVaR model ensures that the lowest return in the worst scenario is maximized to the greatest extent possible, thereby yielding high returns even when the confidence levels are low. The model exploits the diversification approach for risk management and its portfolios contain at least one project from each project category (derivative, platform and breakthrough). The results obtained using max_E_CVaR model can be utilized by decision makers to select and schedule project portfolios according to their risk appetite and acceptable trade-off between risk-averse and risk-neutral objectives.

Keywords Conditional-value-at-risk · Diversification · Project portfolio · Net present value · Risk-averse · Risk-neutral

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1 Introduction

A project portfolio is defined as a group of projects that share and compete for the same resources of an organization. Project portfolios are considered "powerful strategic weapons" for implementing the intended corporate strategy. Thus, to enable the transition of a corporate level strategy to project level strategy, organisations must select projects aligned to their strategies (Archer and Ghasemzadeh 1999; Cleland and Ireland 1999; Shenhar et al. 2000; Liesiö et al. 2007; Meskendahl 2010; Martinsuo 2013). Wheelwright and Clark (1992) categorized projects into breakthrough, platform, derivative, and research and development (R&D) projects and suggested that a project portfolio manager should devise an aggregate project plan by considering a "set" of projects from all the aforementioned categories. This strategy will enable managers to allocate resources and sequence projects, for the short term and build critical development capabilities aligned with corporate strategy for the long term.

Conventional project selection techniques assume the availability of accurate information and use financial metrics such as discounted cash flow, net present value, return on investment and payback period for evaluating projects. However, every project is a unique endeavour and thus obtaining accurate information at the initial project evaluation stage is difficult. This induces uncertainty in the estimation of project cash inflows resulting in financial risk. Further, because the projects operate in complex uncertain environments, they are exposed to different types of risks. The concept of project portfolio management is similar to that of financial asset management. Assets with individual risks and returns are grouped to form a profitable group. An approach of asset diversification is adopted to manage risks. Similarly, project portfolio diversification through selection of projects from different categories (breakthrough, platform, derivative, and R&D), enables organizations to achieve competitive objectives of corporate strategy.

Numerous studies on financial asset management (Rockafellar and Uryasev 2002; Alexander and Baptista 2003; Alexander et al. 2006; Rockafellar et al. 2006; Huang et al. 2010; Yao et al. 2013; Dias 2016; Gülpınar and Çanakoḡlu 2017) have applied the risk measure conditional-value-at-risk (CVaR) to achieve portfolios with a minimum risk of severe low returns and that yield higher returns compared with portfolios obtained through minimization of expected returns. The advantage of CVaR is that it considers the potential risk of severe low returns. CVaR has been adopted as a risk averse measure for assessing risk of portfolios in contexts other than financial asset management. For example, Sawik (2013, 2014) applied CVaR in a supply chain disruption context; Merzifonluoglu (2015) in a supply selection model; Fang et al. (2016) in a supplier selection and Inzunza et al. (2016) in energy source diversification. Hall et al. (2015) revealed that the project portfolios generated by minimizing the underperformance risk were more competitive in achieving the targets than those generated through maximization of expected returns. However, no study in the project portfolio context has incorporated CVaR in objective function to obtain a project portfolio with least risk profile. The present study contributes by addressing this research gap.

The current paper presents a case study of a dairy firm, which has identified 20 potential projects. The study captures the financial risk of the identified projects by using normal distribution for uncertain project cash inflows. In addition, it evaluates the strategic alignment scores and risk scores of technical risk, schedule risk, economic and political risk, organizational risk, statutory clearance risk of the projects by using an Analytical hierarchy process (AHP). Further, it formulates three project portfolio selection and scheduling models namely, risk-neutral (max_E), risk-averse (max_CVaR) and combined compromise (max_E_CVaR) models. The max_E model maximizes the expected total net present value $E(\widetilde{TNPV})$ of the selected and scheduled project portfolios. The max_CVaR model minimizes the risk of obtaining severe low total net present values by maximizing $CVaR_\alpha\left(\widetilde{TNPV}\right)$ for a given confidence level α. The max_E_CVaR model seeks a compromise between the maximization of $E(\widetilde{TNPV})$ and $CVaR_\alpha\left(\widetilde{TNPV}\right)$ by combining them to form a suitable objective function.

Simulation optimization is adopted as a solution methodology. RISKkOptimizer with the OptQuest solver engine of @RISK software is utilized for the implementation of simulation optimization. The results obtained using the three models are analyzed to generate insights for decision-making at varying confidence levels. A comparison of the results obtained using the models shows that the max_CVaR model ensures that the lowest return in the worst scenario is maximized to the greatest extent possible, thereby yielding high returns even when the confidence levels are low. This model exploits the diversification approach for risk management and its portfolios contain at least one project from each project category (derivative, platform and breakthrough). The results obtained using the max_E_CVaR model can be utilized by decision-makers to select and schedule project portfolios according to their risk appetite and acceptable trade-off between risk-averse and risk-neutral objectives.

The remainder of the paper is organized as follows. Section 2 presents a review of the models of project portfolio selection and the identified research gap. Section 3 illustrates the dairy firm case study. Section 4 presents the concept of CVaR. Section 5 presents the project portfolio selection and scheduling model. Section 6 describes the solution methodology. Section 7 presents an analysis of the results obtained using the three models and the generated insights. Finally, Sect. 8 concludes the paper and presents directions for future research.

2 Literature review

This section presents a review of relevant extant literature on project portfolio optimization models and techniques. It first describes the models without risk followed by those with built-in risk aspects.

Doerner et al. (2004) opined that the computational demand of NP-hard multi-objective portfolio selection problems increased with the number of projects and therefore adopted a meta-heuristic Pareto ant colony optimization approach to solve the problem. Ghorbani and Rabbani (2009) proposed a meta-heuristic for a multi-objective project selection problem with two objective functions namely, maximization of the total benefit of the selected projects and minimization of the absolute variation in the allotted resource between each successive time period. Carazo et al. (2010) proposed a multi-objective formulation for obtaining efficient portfolios aligned with the organization objectives. The authors adopted a meta-heuristic procedure based on a scatter search to obtain an optimal schedule for launching the projects under resource constraints and interdependencies. Yu et al. (2012) formulated a multi-criteria project portfolio selection problem in terms of multiple criteria and the decision-maker's preference of criteria and applied a genetic algorithm to devise a feasible and efficient solution. Davoudpour et al. (2012) developed a mathematical model for renewable technology portfolio selection to maximize the support of the organization's strategy and value, while balancing the cost and benefit of the entire portfolio. Chiang and

Nunez (2013) considered project characteristics such as the extent of strategic alignment, benefit, development cost, cross-project synergy, team proficiency and resource availability to maximize the portfolio value of IT organizations.

Lopes and de Almeida (2015) adopted a multi-attribute utility function for selecting a project portfolio in the oil and gas industry by considering three types of synergies: fiscal, design, and information. Fernandez et al. (2015) proposed a method termed as non-outranked ant colony optimization-II, for optimizing portfolio problems, wherein the level of resources allocated to the selected projects had a proportional impact on the benefits obtained. Ghassemi and Amalnick (2018) designed a model for selecting the most fitting new product development projects from a pool of projects while considering reinvestment, loans and initial capital as project funding sources. Although the aforementioned studies have adopted diverse solution methodologies, they have not incorporated the risk aspect of projects in decision-making.

The above limitation was overcome by the following researchers who incorporated risks in objective functions or constraints and adopted approaches such as fuzzy set theory, Monte Carlo simulation, Bayesian modelling, and adjustable robustness. Carlsson et al. (2007) adopted the options approach to develop a fuzzy mixed integer programming model with fuzzy cash flows to maximize the fuzzy net present value of the selected projects. Liesiö et al. (2007) presented a robust portfolio modelling strategy with incomplete cost information and project interdependencies. The authors computed a budget-dependent core index that identified projects that were robust choices at any given budget level. Gemici-Ozkan et al. (2010) developed a decision-support structure for the R&D portfolio selection problem to maximize the expected operating income subject to risk, product interdependency, capacity, and resource allocation constraints. Solak et al. (2010) modelled R&D project portfolios into a multistage stochastic integer program with endogenous uncertainty and developed an efficient solution approach amenable to scenario decomposition. Rabbani et al. (2010) presented a multi-objective particle swarm optimization for the project selection problem with three objectives namely, maximization of total benefits, minimization of total risk and minimization of total cost. Shakhsi-Niaei et al. (2011) presented a two phase framework for project selection. The first phase used Monte Carlo simulation to rank projects based on uncertainty. The second phase derived the final portfolio selection while satisfying the budget, segmentation and other logical constraints by using Monte Carlo simulation linked to an integer programming module.

Ghapanchi et al. (2012) employed a data envelopment analysis for project portfolio selection while incorporating uncertainties and interactions among projects. Hassanzadeh et al. (2014) formulated a binary integer programming model for R&D project portfolio selection with the following competing objectives: maximization of total benefits, minimization of total risk scores, and minimization of total miscellaneous costs. The most preferred solution was obtained using interactive robust weighted Tchebycheff procedure that progressively elicited and incorporated the decision maker's preference information into the solution process. Vilkkumaa et al. (2014) adopted Bayesian modeling for uncertainties in project selection problem to increase the expected future value of the selected portfolio while eliminating the expected gap between the realized ex-post portfolio value and estimated ex-ante portfolio value. Abbassi et al. (2014) proposed a cross-entropy algorithm for selecting balanced portfolios of R&D projects while considering interdependencies and associated market related risks, completion risks and financial risks. Pourahmadi et al. (2015) presented three scenarios- optimistic, normal and pessimistic- for project portfolio selection for maximization of the net present value and minimization of the positive deviations from the allocation of resources.

Hall et al. (2015) considered a project selection problem where each project had an uncertain return. The authors suggested minimization of underperformance riskiness index to minimize the risk of the portfolio return not meeting a specified target. Their results indicated that the project portfolios generated by minimizing the underperformance risk were more competitive in achieving the target than those generated through maximization of expected returns. Yang et al. (2015) proposed a stochastic multiattribute acceptability analysis approach to solve the multiattribute project portfolio optimization problem when information on the importance of attributes is unknown. Perez and Gomez (2016) approached the project portfolio selection and scheduling optimization problem by proposing a nonlinear binary multi-objective mathematical model to maximize contribution by projects. It incorporated the uncertainty that existed in different aspects of decision making by using fuzzy parameters. Fliedner and Liesiö (2016) considered a linear-additive portfolio value function with uncertain parameters and utilized adjustable robustness for multi-attribute project portfolio selection. Liu and Liu (2017) developed a novel parametric credibilistic optimization method for project portfolio selection problem with uncertain returns and work times modelled as parametric possibility distributions. Hu and Szmerekovsky (2017) adopted the news vendor approach to assess the budget requirement of a single project and extended it to project portfolio selection for projects with uncertain budgets.

Most of the aforementioned studies have addressed risks either by maximizing the expected net present value of the uncertain cash inflows or including constraints that place an upper bound on portfolio total risk score. However, no study in the project portfolio optimization context has attempted to minimize the risk of severe low returns by using a risk-averse measure such as CVaR. Numerous studies on financial asset management have applied CVaR to financial portfolio optimization problems to achieve a portfolio with a minimum risk of severe low returns [e.g. Rockafellar and Uryasev (2002), Alexander and Baptista (2003), Alexander et al. (2006), Rockafellar et al. (2006), Huang et al. (2010), Yao et al. (2013), Dias (2016). Gülpınar and Çanakoḡlu (2017)].

CVaR has been adopted as a risk averse measure for assessing risks of portfolios in contexts other than financial asset management. Sawik (2013) applied CVaR to control the risk of the worst-case cost of resilient supply portfolio under disruption risks. Sawik (2014) proposed a stochastic mixed integer programming approach with CVaR for joint supplier selection and customer order scheduling under supply chain disruption risks, for a single or dual sourcing strategy. Merzifonluoglu (2015) utilized CVaR to integrate risk in a supply portfolio selection problem of a firm. Inzunza et al. (2016) proposed a cost-risk model to obtain efficient technology portfolios for energy source diversification. The model constrained the CVaR associated with costs under extreme scenarios of fossil fuel prices. Fang et al. (2016) adopted CVaR to evaluate disruption risks in probability-based multi-criteria optimization model for supplier selection. However, no study in the project portfolio context has incorporated CVaR in objective function to obtain project portfolio with a least-risk profile. The present study overcomes this research gap.

3 A case study of a dairy firm

A case study of a firm, A1 dairy is considered. A1 dairy possessed considerable domestic market share which had stagnated over 5 years. Therefore, it was crucial for the organization to increase its revenue and market share to regain the trust of its investors and compete in the industry. The upper management decided that the organisation should strategically focus on following: (1) New product (NP), (2) market expansion (ME), (3) efficiency improvement (EI), (4) infrastructural development (ID) and (5) environmental and social responsibility (ES). Based on these five strategic focus categories, the following 20 projects (P1 to P20) were identified, as shown in Fig. 1.

- New warehouse project (P1): The project suggested addition of a new warehouse for existing products. The project aimed at efficiency improvement and is categorized as a derivative project.
- Procurement and supplier management system (P2): The project involved installation of a new procurement and supplier management system to assist in documentation and computing for the management of procurement and payment activities of the company. The project aimed at efficiency improvement and is categorized as a derivative project.
- Purchase and installation of latest diary processing equipment (P3): The project involved extension of the existing production set up through purchase and installation of latest diary processing equipment. The project aimed at infrastructure development and is categorized as a derivative project.
- Construction of new retail outlets (P4): The project involved construction of new retail outlets across the country to improve delivery performance. The project aimed at infrastructure development and is categorized as a derivative project.
- Tetra Pak packaging (P5): The project involved introduction of new Tetra Pak packaging for existing milk products. The project aimed at efficiency improvement and is categorized as a derivative project.
- Effluent treatment plant (P6): The project involved setting up of an effluent treatment plant for waste management. The project aimed at fulfilling compulsory environmental regulations and is categorized as a derivative project.

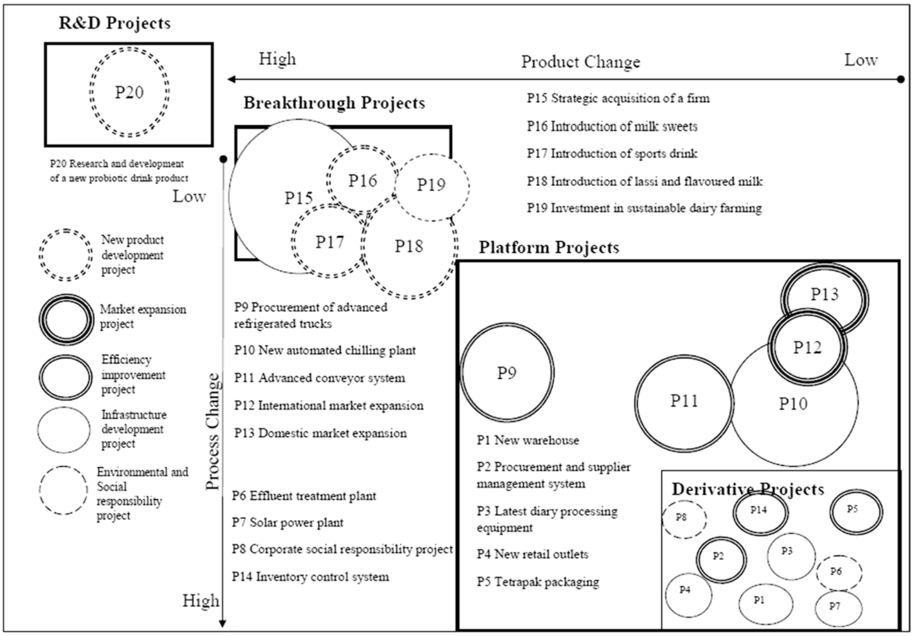

Fig. 1 Projects names, types and strategic categories

- Solar power plant (P7): The project involved setting up of a solar power plant with a capacity of 2 MW capacity. The project aimed at infrastructure development and is categorized as a derivative project.
- Corporate social responsibility project (P8): The project involved contribution of A1 firm to the development of local villages. The project aimed at fulfilling the compulsory social responsibility of the organization and is categorized as a derivative project.
- Procurement of advanced refrigerated trucks (P9): The project involved procurement of advanced refrigerated trucks for competitive logistics. The project aimed at efficiency improvement and is categorized as a platform project.
- New automated chilling plant (P10): The project involved setting up of a new automated chilling plant to increase production. The project aimed at infrastructure development and is categorized as a platform project.
- Advanced conveyor system (P11): The project involved setting up of an advanced conveyor system to reduce production cycle time. The project aimed at efficiency improvement and is categorized as a platform project.
- International (P12) and domestic (P13) market expansion: The projects involved marketing campaigns in international and domestic markets for product promotion. The projects aimed at market expansion and were categorized as platform projects.
- Adoption of an inventory control system (P14): The project involved adoption of an inventory control system for raw materials and finished products. The project aimed at efficiency improvement and is categorized as a derivative project.
- Strategic acquisition of a firm (P15): The project involved strategic acquisition of a firm for the production of new products. The project aimed at infrastructure development and is categorized as a breakthrough project.
- Introduction of milk sweets (P16), sports drink (P17) and lassi and flavored milk (P18): The projects involved increasing the variety of product offerings by the firm in the market. The projects aimed at new product development and were categorized as breakthrough project.
- Investment in sustainable dairy farming (P19): The project involved training programs for farmers for the promotion and adoption of sustainable dairy farming practices in the production processes. The project aimed at fulfilling the environmental responsibility of A1 firm and is categorized as breakthrough project.
- R&D of a new probiotic drink product (P20): The project aimed at R&D of a new probiotic drink product for medical use.

The projects incur high cash outflows (c_i), therefore it is crucial for the organization to select projects that align with the strategy, have minimum risk exposure, and yield maximum expected total net present value. Projects P6 and P8 are mandatory due to government regulations and social responsibility. The total investment required for the 20 identified projects is USD 2000. But the organization has total budget availability of only USD 700, equally spread over four stages (Inv_{s_1} to Inv_{s_4} all equal to USD 175) each with five time units ($s_1 = \{1, 2, 3, 4, 5\}$; $s_2 = \{6, 7, 8, 9, 10\}$; $s_3 = \{11, 12, 13, 14, 15\}$; $s_4 = \{16, 17, 18, 19, 20\}$). The weighted average cost of capital for the firm is estimated to be $wacc = 10\%$.

Table 1 shows the notations that are used in the subsequent sections.

Table 1 Definition of notations

$T = \{1, 2, 3 \ldots 20\}$	Set of time units
$s_1 = \{1, 2, 3, 4, 5\}$	Set of time units for the first investment stage
$s_2 = \{6, 7, 8, 9, 10\}$	Set of time units for the second investment stage
$s_3 = \{11, 12, 13, 14, 15\}$	Set of time units for the third investment stage
$s_4 = \{16, 17, 18, 19, 20\}$	Set of time units for the fourth investment stage
t	Index for time unit
$I = \{1, 2, 3 \ldots ..20\}$	Set of projects
i	Index for projects
Inv_{s_1}	Investment available for the first stage
Inv_{s_2}	Investment available for the second stage
Inv_{s_3}	Investment available for the third stage
Inv_{s_4}	Investment available for the fourth stage
o_{s_1}	Unutilized investment of the first stage overflowing to the second stage
o_{s_2}	Unutilized investment of the second stage overflowing to the third stage
o_{s_3}	Unutilized investment of the third stage overflowing to the fourth stage
c_i	Initial investment required for project i
$n \in \{1, 2, 3, \ldots 10\}$	Index for cash inflow
$n\_\widetilde{in\_cash}_i$	nth uncertain cash inflow from project i
$n\_\widetilde{in\_cash}_i(\mu)$	Mean of normal distribution of nth cash inflow from project i
$n\_\widetilde{in\_cash}_i(\sigma)$	Standard deviation of normal distribution of nth cash inflow from project i
$wacc$	Weighted average cost of capital of the firm
st_sc_i	Strategic alignment score of project i
st_min	Minimum acceptable total strategic alignment score of portfolio
$Tech\_risk_i$	Technical risk score of project i
w_{Tech_risk}	Weightage assigned to the technical risk
Sch_risk_i	Schedule risk score of project i
w_{Sch_risk}	Weightage assigned to the schedule risk
EP_risk_i	Economic and political risk score of project i
w_{EP_risk}	Weightage assigned to the economic and political risk
Org_risk_i	Organizational risk score of project i
w_{Org_risk}	Weightage assigned to the organizational risk
Stc_risk_i	Statutory clearance risk score of project i
w_{Stc_risk}	Weightage assigned to the statutory clearance risk
$risk\_max$	Maximum acceptable total risk score of portfolio
$\widetilde{NPV}_i$	Net present value of project i
$\widetilde{TNPV}$	Total net present value of project portfolio
$E(\widetilde{TNPV})$	Expected total net present value of project portfolio
α	Confidence level at which analysis is performed
$VaR_\alpha\left(\widetilde{TNPV}\right)$	Value-at-risk of total net present value of project portfolio at confidence level α
$CVaR_\alpha\left(\widetilde{TNPV}\right)$	Conditional-value-at-risk of total net present value of project portfolio at confidence level α
λ	Weightage of E_TNPV in the objective function of the composite compromise model
x_{it}	Decision variable such that $x_{it} = \begin{cases} 1 & \text{if project } i \text{ is launched at time } t \\ 0 & \text{otherwise} \end{cases}$

3.1 Strategic alignment scores

Because project portfolios are formulated to achieve the intended corporate strategy, it is crucial to ensure that the selected projects align with the organizational goals. Therefore, the identified projects are evaluated to obtain their strategic alignment scores st_sc_i. The projects in the five strategic focus categories are compared using AHP based on the upper management's judgement. Table 2 shows the pairwise comparison matrix and computed strategic alignment scores. The highest importance is given to NP development projects to attract more customers by offering diversified products. The second highest importance is given to ME projects to increase the market share and sales, followed by EI projects, ID and ES projects in that order. To ensure strategic alignment of the selected project portfolio, the upper management suggested that it should have the total strategic alignment score greater than or equal to $st\_min = 2$.

3.2 Uncertain cash inflows

Another important aspect of projects is their exposure to different types of risks. Every project is a unique endeavour, and thus, obtaining accurate information at the initial project evaluation stage is difficult. This induces uncertainty in the estimation of cash inflows of the project resulting in financial risk. Therefore, the present study captures the cash inflows of the projects by using normal distribution, such that the nth uncertain cash inflow from project i ($\widetilde{n\_in\_cash_i}$) has mean $\widetilde{n\_in\_cash_i}(\mu)$ and standard deviation $\widetilde{n\_in\_cash_i}(\sigma)$.

3.3 Risk scores

Because the projects operate in complex uncertain environment, they are also associated with different risk types namely technical risk ($Tech\_risk$), schedule risk (Sch_risk), economic and political risk (EP_risk), organizational risk (Org_risk) and statutory clearance risk (Stc_risk), as shown in Table 3. However, the weightage of each risk is different and the severity of risks varies across projects. Therefore, weights of the risks are calculated using the AHP based on the upper management's judgement regarding their relative importance. Table 4 presents the pairwise comparison matrix and computed weights of technical risk (w_{Tech_risk}), schedule risk $\left(w_{Sch\_risk}\right)$, economic and political risk $\left(w_{EP\_risk}\right)$, organizational risk $\left(w_{Org\_risk}\right)$ and statutory clearance risk $\left(w_{Stc\_risk}\right)$. The highest importance is given to economic and political risk followed by technical risk, schedule risk, statutory clearance risk and organizational risk in that order. Additionally, the upper management and risk experts of the domain examined each risk with respect to each project and assigned a score based on the severity of risk ($Tech\_risk_i$; Sch_risk_i; EP_risk_i;Org_risk_i; Stc_risk_i) as shown in Table 5. The risk score of a project is

Table 2 Strategic alignment scores

	NP	ME	EI	ID	ES	st_sc_i
NP	1	3	5	7	9	0.503
ME	0.333	1	3	5	7	0.26
EI	0.2	0.333	1	3	5	0.134
ID	0.143	0.2	0.333	1	3	0.068
ES	0.111	0.143	0.2	0.333	1	0.035

Table 3 Project risks

Technical risk	Schedule risk	Economic and political risk	Organizational risk	Statutory clearance risk
Equipment risk	Project delay risk	Change in Government policy risk	Supplier risk	Land acquisition risk
Technology selection risk	Improper estimates risk	Inflation risk	Contractor risk	Environmental clearance risk
Engineering and design change risk				

computed as the weighted sum of its individual risks. The total risk score of the portfolio is the sum of risk scores of all the selected projects. To ensure that the risk exposure of the firm is within the acceptable limit, the upper management suggested that the selected project portfolio should have a total weighted risk score less than or equal to $risk\_max = 100$.

4 Risk measure CVaR

The net present value of project i which is launched at time unit t is given by Eq. (1)

$$\widetilde{NPV}_i = \left(\frac{-c_i}{(1 + wacc)^{\left(\sum_{t\epsilon T} t \times x_{it}\right)}} + \sum_{n=1}^{10} \frac{\widetilde{in\_cash}_i(n)}{(1 + wacc)^{\left(\sum_{t\epsilon T} t \times x_{it}\right) + n}} \right) \times \sum_{t \in T} x_{it} \tag{1}$$

where x_{it} is the decision variable such that $x_{it} = \begin{cases} 1 & \text{if project } i \text{ is launched at time } t \\ 0 & \text{otherwise} \end{cases}$

The total net present value $\widetilde{TNPV}$ of the project portfolio is the sum of $\widetilde{NPV}_i$ of all projects and is given by Eq. (2)

$$\widetilde{TNPV} = \sum_{i \in I} \widetilde{NPV}_i \tag{2}$$

Two metrics widely used to quantify risk are value-at-risk (VaR) and CVaR (Nguyen and Le 2015). For confidence level $0 \le \alpha < 1$, $VaR_\alpha\left(\widetilde{TNPV}\right)$ is the $(1-\alpha)$-quantile of the $\widetilde{TNPV}$ distribution which is the largest value that ensures that the probability of obtaining a $TNPV$ less than this value is lower than $(1-\alpha)\epsilon(0, 1)$.

$$VaR_\alpha\left(\widetilde{TNPV}\right) = \max\left\{ TNPV \in R \,:\, P\left(\widetilde{TNPV} < TNPV\right) \le (1-\alpha) \right\}$$

where, R is the support of probability distribution of $\widetilde{TNPV}$

CVaR at confidence level $\alpha \left(CVaR_\alpha\right)$ is defined as the expected value of $\widetilde{TNPV}$ smaller than the $(1-\alpha)$-quantile of the probability distribution of $\widetilde{TNPV}$ as shown in Eq. (3).

$$\begin{aligned} CVaR_\alpha\left(\widetilde{TNPV}\right) &= \mathbb{E}\left\{ \widetilde{TNPV} | \widetilde{TNPV} \le VaR_\alpha\left(\widetilde{TNPV}\right) \right\} \\ &= \frac{1}{(1-\alpha)} \int_{-\infty}^{VaR_\alpha\left(\widetilde{TNPV}\right)} TNPVF\left(\widetilde{TNPV}\right) dTNPV \end{aligned} \tag{3}$$

where, $F\left(\widetilde{TNPV}\right)$ is the probability density function of the total net present value.

Although VaR is widely used as a risk measure, it has following disadvantages. It does not meet the conditions of sub-additivity and non-convexity for non-normal probability distributions. Moreover, VaR does not consider the potential risk of severe low returns. CVaR overcomes these limitations. It is a coherent risk measure with desirable properties of convexity and monotonicity with respect to stochastic dominance of order one. Moreover, it considers the potential risk of severe low returns (Pflug 2000; Rockafellar and Uryasev 2002; Ogryczak and Ruszczynski 2002).

5 Project portfolio selection and scheduling model

Three project portfolio selection and scheduling models namely risk-neutral model (max_E), risk-averse model (max_CVaR) and combined compromise model (max_E_CVaR) are formulated. The objective functions of the three models are defined as follows.

max_E model: Maximize the expected TNPV: $maximize\ E\left(\widetilde{TNPV}\right)$

max_CVaR model: Minimize the risk of obtaining severe low TNPV: $maximize\ CVaR_\alpha\left(\widetilde{TNPV}\right)$

max_E_CVaR: Maximize the weighted sum of expected TNPV and $CVaR_\alpha\left(\widetilde{TNPV}\right)$: $maximize\left(\lambda E\left(\widetilde{TNPV}\right) + (1-\lambda)CVaR_\alpha\left(\widetilde{TNPV}\right)\right)$

where, λ is the weightage given to E_TNPV.
subject to constraints
Equation (4) indicates that a project should be selected only once.

$$\sum_{t\in T} x_{it} \le 1 \quad \forall i \in I \tag{4}$$

Equations (5), (6), (7) and (8) are stage budget constraints and indicate that the total investment in a stage should be less than or equal to the investment available in that stage.

$$\sum_{i\in I} c_i \sum_{t=1}^{5} x_{it} + o_{s_1} \le Inv_{s_1} \tag{5}$$

$$\sum_{i\in I} c_i \sum_{t=6}^{10} x_{it} + o_{s_2} \le Inv_{s_2} + o_{s_1} \tag{6}$$

Table 4 Weightages of risks

	Tech_risk	*Sch_risk*	*EP_risk*	*Org_risk*	*Stc_risk*	*Weightage*
Tech_risk	1	3	0.33	7	5	0.260225
Sch_risk	0.33	1	0.2	5	3	0.13435
EP_risk	3	5	1	9	7	0.502825
Org_risk	0.143	0.2	0.11	1	0.33	0.03482
Stc_risk	0.2	0.33	0.143	3	1	0.06778

Table 5 Projects data

Project number	st_sc_i	$Tech\_risk_i$	Sch_risk_i	EP_risk_i	Org_risk_i	Stc_risk_i	c_i
P1	0.068	1	1	5	3	5	−75
P2	0.134	3	1	3	5	1	−5
P3	0.068	3	1	3	3	5	−80
P4	0.068	1	1	1	1	5	−15
P5	0.134	3	1	1	5	7	−85
P6	0.035	1	1	1	1	1	−30
P7	0.068	1	3	1	1	3	−20
P8	0.035	0	1	1	1	1	−10
P9	0.134	5	5	3	3	5	−160
P10	0.068	5	5	5	3	5	−175
P11	0.134	5	5	3	5	5	−85
P12	0.260	5	5	5	5	7	−140
P13	0.260	5	5	3	5	5	−100
P14	0.134	5	7	3	5	1	−105
P15	0.503	7	7	5	5	5	−285
P16	0.503	7	7	3	5	7	−125
P17	0.503	7	7	5	7	7	−105
P18	0.503	7	7	3	5	7	−120
P19	0.134	7	7	1	7	1	−130
P20	0.503	9	9	3	1	1	−150

Project number	$1\_\widetilde{in\_cash_i}(\mu)$	$2\_\widetilde{in\_cash_i}(\mu)$	$3\_\widetilde{in\_cash_i}(\mu)$	$4\_\widetilde{in\_cash_i}(\mu)$	$5\_\widetilde{in\_cash_i}(\mu)$	$6\_\widetilde{in\_cash_i}(\mu)$	$7\_\widetilde{in\_cash_i}(\mu)$	$8\_\widetilde{in\_cash_i}(\mu)$	$9\_\widetilde{in\_cash_i}(\mu)$	$10\_\widetilde{in\_cash_i}(\mu)$
P1	10	10	12	15	18	20	15	10	10	8
P2	3	4	4	4	4					
P3	10	12	14	16	18	18	16	14	12	10

Table 5 (continued)

Project number	$1\_\widetilde{in\_cash_i}(\mu)$	$2\_\widetilde{in\_cash_i}(\mu)$	$3\_\widetilde{in\_cash_i}(\mu)$	$4\_\widetilde{in\_cash_i}(\mu)$	$5\_\widetilde{in\_cash_i}(\mu)$	$6\_\widetilde{in\_cash_i}(\mu)$	$7\_\widetilde{in\_cash_i}(\mu)$	$8\_\widetilde{in\_cash_i}(\mu)$	$9\_\widetilde{in\_cash_i}(\mu)$	$10\_\widetilde{in\_cash_i}(\mu)$
P4	2	3	4	4	5	5	4	4	3	2
P5	10	12	15	18	18	20	20	18	15	12
P6	0	0	0	0	0	0	0	0	0	0
P7	2	2	4	4	4	6	6	6	8	8
P8	0	0	0	0	0	0	0	0	0	0
P9	20	22	25	30	35	30	30	27	22	20
P10	10	25	30	32	35	40	40	35	32	30
P11	12	15	18	20	22	20	18	15	12	12
P12	22	26	30	32	36	40	44	48	50	52
P13	14	16	20	24	26	30	32	38	42	45
P14	30	35	40	40	45					
P15	0	45	64	76	90	105	110	125	130	150
P16	22	25	28	30	35	35	35	35	30	30
P17	0	20	20	25	30	35	35	40	45	40
P18	0	30	30	30	32	34	26	24	25	26
P19	0	25	30	30	35	35	40	40	40	45
P20	0	0	20	25	30	35	40	45	45	50
Project number	$1\_\widetilde{in\_cash_i}(\sigma)$	$2\_\widetilde{in\_cash_i}(\sigma)$	$3\_\widetilde{in\_cash_i}(\sigma)$	$4\_\widetilde{in\_cash_i}(\sigma)$	$5\_\widetilde{in\_cash_i}(\sigma)$	$6\_\widetilde{in\_cash_i}(\sigma)$	$7\_\widetilde{in\_cash_i}(\sigma)$	$8\_\widetilde{in\_cash_i}(\sigma)$	$9\_\widetilde{in\_cash_i}(\sigma)$	$10\_\widetilde{in\_cash_i}(\sigma)$
P1	1.68	1.68	2.01	2.51	3.02	3.35	2.51	1.68	1.68	1.34
P2	0.40	0.47	0.53	0.53	0.53	0.00	0.00	0.00	0.00	0.00
P3	1.43	1.72	2.01	2.29	2.58	2.58	2.29	2.01	1.72	1.43
P4	0.13	0.19	0.25	0.25	0.32	0.32	0.25	0.25	0.19	0.13
P5	1.03	1.24	1.55	1.86	1.86	2.07	2.07	1.86	1.55	1.24
P6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 5 (continued)

Project number	$1\_\widetilde{in\_cash_i}(\sigma)$	$2\_\widetilde{in\_cash_i}(\sigma)$	$3\_\widetilde{in\_cash_i}(\sigma)$	$4\_\widetilde{in\_cash_i}(\sigma)$	$5\_\widetilde{in\_cash_i}(\sigma)$	$6\_\widetilde{in\_cash_i}(\sigma)$	$7\_\widetilde{in\_cash_i}(\sigma)$	$8\_\widetilde{in\_cash_i}(\sigma)$	$9\_\widetilde{in\_cash_i}(\sigma)$	$10\_\widetilde{in\_cash_i}(\sigma)$
P7	0.14	0.14	0.28	0.28	0.28	0.42	0.42	0.42	0.56	0.56
P8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P9	3.92	4.32	4.91	5.89	6.87	5.89	5.89	5.30	4.32	3.92
P10	2.46	6.16	7.39	7.89	8.63	9.86	9.86	8.63	7.89	7.39
P11	2.40	3.00	3.59	3.99	4.39	3.99	3.59	3.00	2.40	2.40
P12	5.65	6.68	7.70	8.22	9.24	10.27	11.30	12.32	12.84	13.35
P13	2.80	3.20	3.99	4.79	5.19	5.99	6.39	7.59	8.39	8.99
P14	5.99	6.98	7.98	7.98	8.98	0.00	0.00	0.00	0.00	0.00
P15	0.00	13.02	18.52	22.00	26.05	30.39	31.84	36.18	37.63	43.41
P16	5.41	6.15	6.89	7.38	8.61	8.61	8.61	8.61	7.38	7.38
P17	0.00	5.99	5.99	7.49	8.99	10.49	10.49	11.99	13.49	11.99
P18	0.00	7.38	7.38	7.38	7.87	8.36	6.39	5.90	6.15	6.39
P19	0.00	4.47	5.36	5.36	6.26	6.26	7.15	7.15	7.15	8.05
P20	0.00	0.00	5.16	6.45	7.74	9.03	10.32	11.61	11.61	12.90

$$\sum_{i \in I} c_i \sum_{t=11}^{15} x_{it} + o_{s_3} \leq Inv_{s_3} + o_{s_2} \tag{7}$$

$$\sum_{i \in I} c_i \sum_{t=16}^{20} x_{it} \leq Inv_{s_4} + o_{s_3} \tag{8}$$

Equation (9) indicates that the mandatory projects, P6 and P8, must be selected.

$$\sum_{t \in T} x_{6t} + \sum_{t \in T} x_{8t} = 2 \tag{9}$$

Equation (10) indicates that the total strategic score of the portfolio should be greater than or equal to the minimum acceptable strategic alignment score.

$$\sum_{i \in I} st\_sc_i \sum_{t \in T} x_{it} \geq st\_min \tag{10}$$

Equation (11) indicates that the total risk of the portfolio should be less than or equal to the maximum acceptable risk.

$$\begin{aligned} & w_{Tech\_risk} \sum_{i \in I} Tech\_risk_i \sum_{t \in T} x_{it} + w_{Sch\_risk} \sum_{i \in I} Sch\_risk_i \sum_{t \in T} x_{it} \\ & + w_{EP\_risk} \sum_{i \in I} EP\_risk_i \sum_{t \in T} x_{it} + w_{Org\_risk} \sum_{i \in I} Org\_risk_i \sum_{t \in T} x_{it} \\ & + w_{Stc\_risk} \sum_{i \in I} Stc\_risk_i \sum_{t \in T} x_{it} \leq risk\_max \end{aligned} \tag{11}$$

6 Solution methodology

Simulation optimization is used as a solution methodology for the formulated project portfolio selection and scheduling model. It incorporates uncertainties in the input parameters and uses a combination of simulation and meta-heuristic search algorithm to optimize a static (e.g. mean, variance, VaR, CVaR) as an objective function. The process starts with the generation of a trial solution. With an initial set of values of decision variables in the trial solution, model simulation is performed where random values of input parameters are generated using Latin hypercube sampling (LHS), from their probability distribution. The advantage of using LHS is that unlike simple random sampling, LHS ensures full coverage of the range of each variable by maximally stratifying each marginal distribution (Iman and Conover 1982). The simulation generates a distribution of the possible outcomes of the objective function. If during simulation any constraint is not satisfied then the simulation is stopped and a new trial solution to be simulated is generated. For the subsequent simulations, a meta-heuristics search algorithm generates more trial solutions. The process stops when the stopping criteria (e.g. number of trial solutions, time elapsed) specified by the user is met. The trial solution that provides the highest value of the static of the objective function is selected as the solution of the problem.

In this study, RISKOptimizer with OptQuest solver engine of @RISK software is used for simulation optimization. RISKOptimizer employs Monte Carlo simulation with LHS (from @RISK) to address the uncertainty present in the input parameters of the model. Further, the OptQuest solving engine combines Tabu search, scatter search, integer programming, and neural networks into a single, composite search algorithm that provides maximum efficiency in identifying new trial solutions (Glover et al. 1998; Palisade corporation 2010). OptQuest with scatter search as the optimization engine was first developed by F. Glover, J. P. Kelly and M. Laguna at the University of Colorado (Laguna 1997). Subsequently, scatter search was coupled with tabu search strategies to obtain high quality solutions. The OptQuest Engine assumes objective as a complex function that is computationally expensive to calculate and is represented as a black box. Therefore, OptQuest uses a neural network as a prediction model to help the system accelerate the search by avoiding calls to the expensive black-box. The objective function values of trial solutions visited during the search are collected for a number of iterations. These data points are then used to train a multi-layered neural network.

In this study, 100,000 random trial solutions (both feasible and non-feasible) were generated using OptQuest. For each solution Monte Carlo simulation is performed to evaluate $\widetilde{TNPV}$ and thereafter $E\left(\widetilde{TNPV}\right)$ and $CVaR_{\alpha}\left(\widetilde{TNPV}\right)$. The solution that yields the best objective function value is accepted as the final solution. Figure 2 presents the steps of the simulation optimization.

7 Result analysis

The aforementioned simulation methodology is applied in max_E, max_CVaR and max_E_CVaR models. Each model run explores 100,000 trial solutions. The max_E model is run only once which yields maximum objective function $E\left(\widetilde{TNPV}\right)$ of the selected and scheduled project portfolio and calculates $CVaR_{\alpha}\left(\widetilde{TNPV}\right)$, and $VaR_{\alpha}\left(\widetilde{TNPV}\right)$ corresponding to multiple confidence levels $\alpha \epsilon \{90\%, 92.5\%, 95\%, 97.5\%, 99\%\}$ from the obtained probability distribution of $\widetilde{TNPV}$. The max_CVaR model was run five times for confidence levels $\alpha \epsilon \{90\%, 92.5\%, 95\%, 97.5\%, 99\%\}$. Each model yields maximum objective function $CVaR_{\alpha}\left(\widetilde{TNPV}\right)$ for the corresponding α value and calculates $E\left(\widetilde{TNPV}\right)$ of the selected project portfolio.

Tables 6 and 7 present the outputs obtained from the max_CVaR and max_E models. Table 6 presents the values of $VaR_{\alpha}\left(\widetilde{TNPV}\right)$, $CVaR_{\alpha}\left(\widetilde{TNPV}\right)$ and $E\left(\widetilde{TNPV}\right)$ of the selected and scheduled project portfolio corresponding to the aforementioned confidence levels. Table 7 presents the selected projects and their launch dates (time units t).

Figure 3 reveals that the max_CVaR model yields $E\left(\widetilde{TNPV}\right)$ greater than or equal to that of the max_E model (except $\alpha = 99\%$). Moreover, the risk measures $VaR_{\alpha}\left(\widetilde{TNPV}\right)$, and $CVaR_{\alpha}\left(\widetilde{TNPV}\right)$ are higher for the max_CVaR model than that of max_E model. This indicates that the max_CVaR model pushes the entire $\widetilde{TNPV}$ probability distribution toward the right, as shown in Fig. 4, to increase all the three $\left(\widetilde{TNPV}\right)$, $VaR_{\alpha}\left(\widetilde{TNPV}\right)$ and

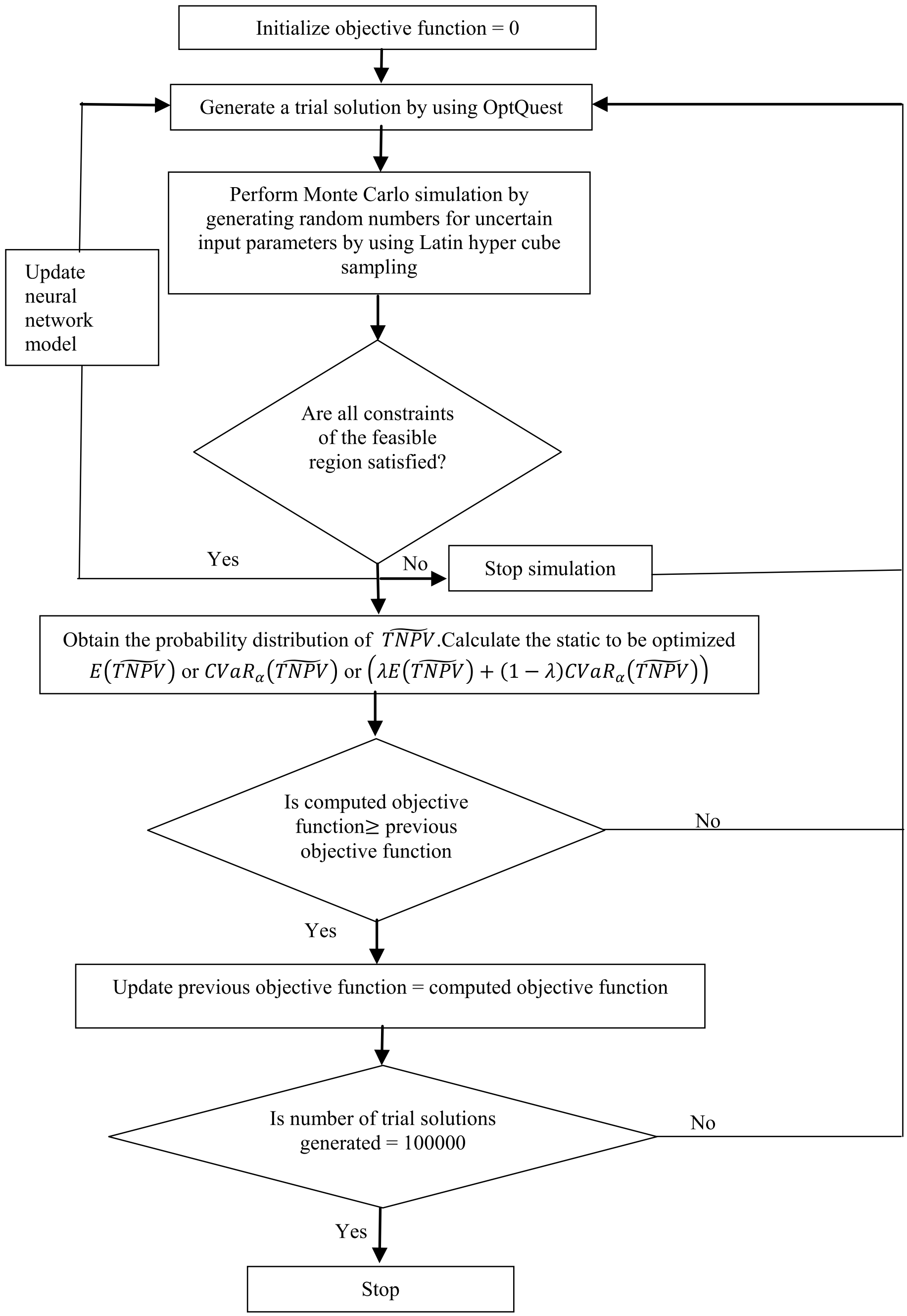

Fig. 2 Steps of simulation optimization

Table 6 Outputs of the max_CVaR and max_E models

Confidence level α	Max_E model			Max_CVaR model		
	$VaR_\alpha\left(\widetilde{TNPV}\right)$	$CVaR_\alpha\left(\widetilde{TNPV}\right)$	$E\left(\widetilde{TNPV}\right)$	$VaR_\alpha\left(\widetilde{TNPV}\right)$	$CVaR_\alpha\left(\widetilde{TNPV}\right)$	$E\left(\widetilde{TNPV}\right)$
90%	125.0263	121.8016	157.4432	132.3762	128.6804	172.2913
92.5%	125.0263	120.1893	157.4432	133.0976	132.3736	160.0914
95%	121.7995	118.579	157.4432	134.8063	129.8087	156.3705
97.5%	118.579	118.579	157.4432	135.1246	135.1246	161.8208
99%	118.579	118.579	157.4432	130.4083	130.4083	151.8088

$CVaR_\alpha\left(\widetilde{TNPV}\right)$. This ensures that the lowest TNPV in the worst scenario is maximized to the greatest extent possible thereby yielding higher returns even when the confidence levels are low.

Further, Fig. 3 shows that the differences in the values of $VaR_\alpha\left(\widetilde{TNPV}\right)$ and $CVaR_\alpha\left(\widetilde{TNPV}\right)$ in max_CVaR model and max_E model are higher for higher confidence levels ($\alpha = 95\%\ , 97.5\%\ , 99\%$) than for lower confidence levels ($\alpha = 90\%\ , 92.5\%$). This finding evidences the advantage of using the max_CVaR model in risk averse decision making at higher confidence levels.

Figure 5 shows that the max_CVaR model selected total number of projects that is higher than or equal to that of the max_E model. This indicates that the max_CVaR model attempts to minimize risk by increasing the number of selected projects. For the max_CVaR model with lower confidence levels ($\alpha = 90\%\ , 92.5\%$), the composition of the selected project portfolio with respect to number of projects in each category is similar to that of the max_E model (derivative = 2, platform = 2, breakthrough = 2). However, as the confidence level increases ($\alpha = 95\%\ , 97.5\%\ , 99\%$) the composition varies with an increase in the number of derivative and breakthrough projects selected (derivative = 3, Breakthrough = 3). The above observations demonstrate that, for lower confidence levels, the max_CVaR model behaves similar to the max_E model. However, as the risk appetite decreases (increase in confidence levels) the behavior of the max_CVaR model differs from that of the max_E model. This indicates that the max_CVaR model utilizes diversification approach for risk management.

As shown in Table 6, the composition of the portfolios obtained from both the models consists of P2, P4, P6, P7, P8, P12, P13, P15, P16, P17 and P19. P 2 "setting up procurement and supplier management system" a derivative project, is selected by all the models and is scheduled to be launched by most of the models in the first stage. P6 "Setting up effluent treatment plant" and P8 "Corporate social responsibility project" are mandatory projects and are scheduled to be started on the last stage at time unit 20, as they generate no cash inflows but require initial investment. P13 "Domestic market expansion" a platform project is selected by all the models and is scheduled to be launched by most of the models in the intermediate stages i.e. second or third stage. P17 "Introduction of sports drink" a breakthrough project is selected by all the models and is scheduled to be launched by most of the models in the later stages (i.e. fourth or fifth stage). The aforementioned project selection demonstrates that the obtained portfolios contain at least one project from each project category (derivative, platform

Table 7 Selected projects and their launch dates

Model	Selected projects and their launch date (time units t)											Selected number of projects				
												Derivative	Platform	Breakthrough	Compulsory	Total
max_E model	P 2, t = 3		P 6, t = 20	P 7, t = 1	P 8, t = 20	P 12, t = 18	P 13, t = 11	P 15, t = 6		P 17, t = 12		2	2	2	2	8
max_CVaR α = 99%	P 2, t = 11	P 4, t = 1	P 6, t = 20	P 7, t = 3	P 8, t = 20		P 13, t = 6	P 15, t = 17	P 16, t = 1	P 17, t = 11		3	1	3	2	9
max_CVaR α = 97.5%	P 2, t = 8	P 4, t = 1	P 6, t = 20	P 7, t = 4	P 8, t = 20	P 12, t = 1	P 13, t = 11		P 16, t = 6	P 17, t = 11	P 19, t = 16	3	2	3	2	10
max_CVaR α = 95%	P 2, t = 1	P 4, t = 13	P 6, t = 20	P 7, t = 11	P 8, t = 20	P 12, t = 6	P 13, t = 6		P 16, t = 17	P 17, t = 2	P 19, t = 11	3	2	3	2	10
max_CVaR α = 92.5%	P 2, t = 1	P 4, t = 1	P 6, t = 20		P 8, t = 20	P 12, t = 3	P 13, t = 11	P 15, t = 16		P 17, t = 6		2	2	2	2	8
max_CVaR α = 90%	P 2, t = 1		P 6, t = 20	P 7, t = 1	P 8, t = 20	P 12, t = 1	P 13, t = 16	P 15, t = 11		P 17, t = 16		2	2	2	2	8

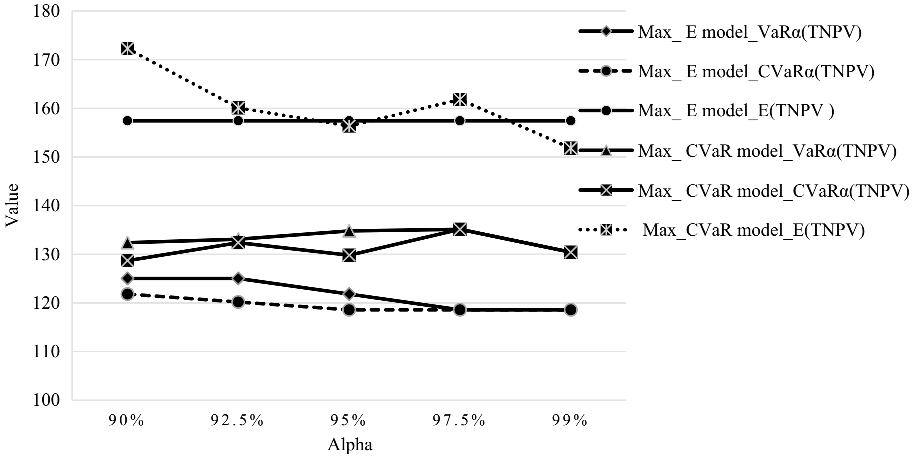

Fig. 3 The max_CVaR model versus max_E model

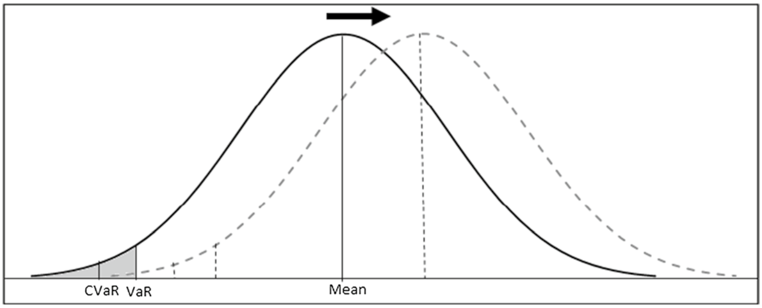

Fig. 4 Effect of max_CVaR model

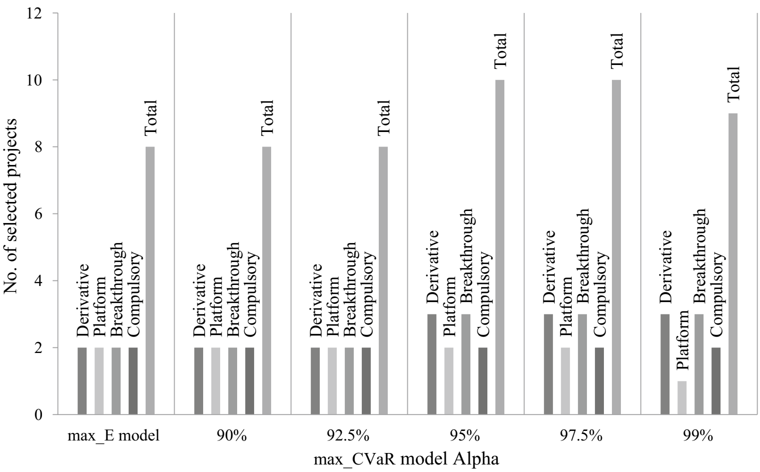

Fig. 5 Number of projects selected in each category

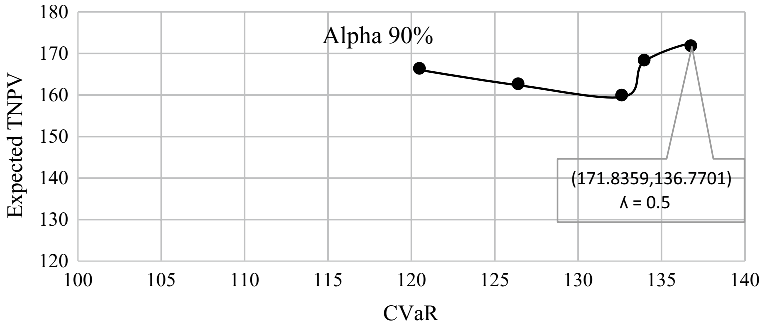

Fig. 6 Trade-off between $E\left(\widetilde{TNPV}\right)$ and $CVaR_{90\%}\left(\widetilde{TNPV}\right)$

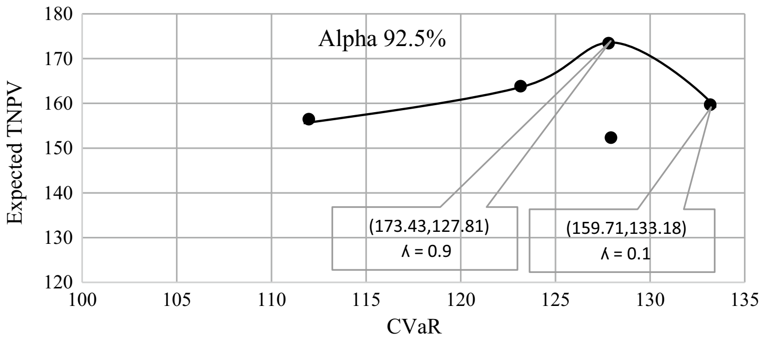

Fig. 7 Trade-off between $E\left(\widetilde{TNPV}\right)$ and $CVaR_{92.5\%}\left(\widetilde{TNPV}\right)$

and breakthrough) which is in accordance with the aggregate project plan suggested by Wheelwright and Clark (1992). Projects P1, P3, P5, P9, P10, P11, P14, P18, and P20 are never selected by any model.

The max_E_CVaR model is run 5×5 times for all combinations of confidence levels $\alpha \epsilon \{90\%, 92.5\%, 95\%, 97.5\%, 99\%\}$ and lambda values $\lambda \epsilon \{0.1, 0.3, 0.5, 0.7, 0.9\}$. Each model yields the maximum objective function $\left(\lambda E\left(\widetilde{TNPV}\right) + (1-\lambda) CVaR_{\alpha}\left(\widetilde{TNPV}\right)\right)$ for corresponding α and λ values. Figures 6, 7, 8, 9 and 10 display the trade-off between $E\left(\widetilde{TNPV}\right)$ and $CVaR_{\alpha}\left(\widetilde{TNPV}\right)$ as weightage factor λ is varied for each value of α.

Figure 6 shows that for confidence level, $\alpha = 90\%$ the best trade-off between $E\left(\widetilde{TNPV}\right)$ and $CVaR_{90\%}\left(\widetilde{TNPV}\right)$ is obtained for $\lambda = 0.5$ with $E\left(\widetilde{TNPV}\right) = 171.8359$ and $CVaR_{90\%}\left(\widetilde{TNPV}\right) = 136.7701$. For $\alpha = 92.5\%$ in Fig. 7 two solution points corresponding to $\lambda = 0.1$ and 0.9 are identified as trade-offs points. A decision maker who is neutral towards risk will choose the solution with higher expected total net present value $E\left(\widetilde{TNPV}\right) = 173.43$ and $CVaR_{92.5\%}\left(\widetilde{TNPV}\right) = 127.81$ at $\lambda = 0.9$. By contrast, a risk averse decision maker will select the solution with a higher $CVaR_{92.5\%}\left(\widetilde{TNPV}\right) = 133.18$

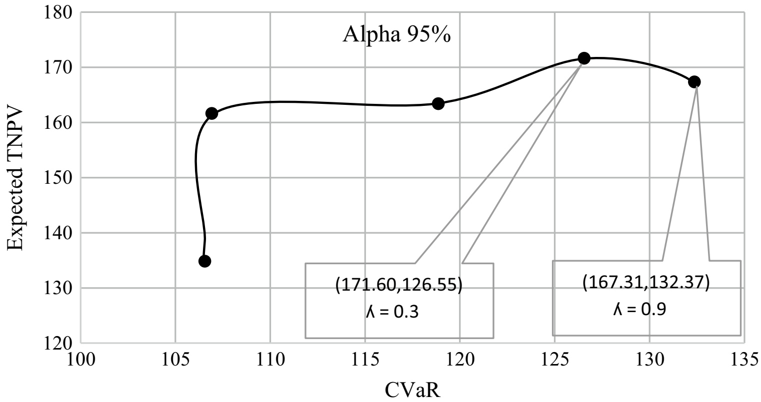

Fig. 8 Trade-off between $E\left(\widetilde{TNPV}\right)$ and $CVaR_{95\%}\left(\widetilde{TNPV}\right)$

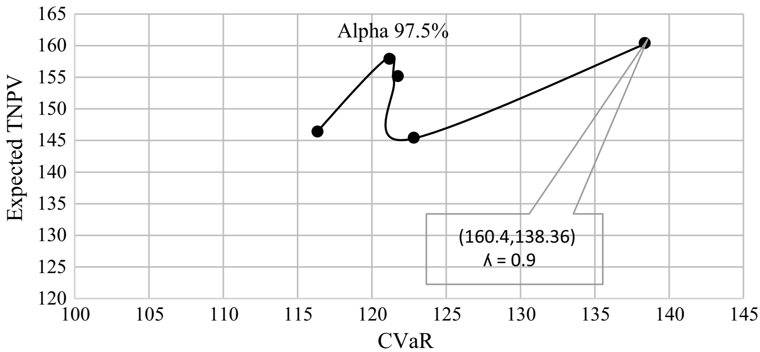

Fig. 9 Trade-off between $E\left(\widetilde{TNPV}\right)$ and $CVaR_{97.5\%}\left(\widetilde{TNPV}\right)$

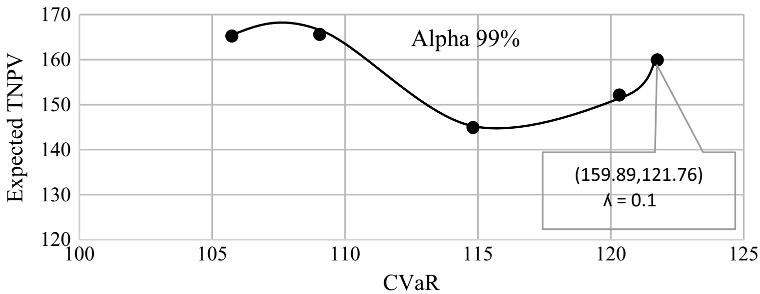

Fig. 10 Trade-off between $E\left(\widetilde{TNPV}\right)$ and $CVaR_{99\%}\left(\widetilde{TNPV}\right)$

and $E\left(\widetilde{TNPV}\right) = 159.71$ at $\lambda = 0.1$. Similarly, for $\alpha = 95\%$ in Fig. 8 shows two trade-off points risk averse ($\lambda = 0.3, CVaR_{95\%}\left(\widetilde{TNPV}\right) = 126.55, E\left(\widetilde{TNPV}\right) = 171.60$ and risk neutral $\left(\lambda = 0.3, E\left(\widetilde{TNPV}\right) = 167.31, CVaR_{95\%}\left(\widetilde{TNPV}\right) = 132.37,\right)$ are obtained. Figures 9 and 10 show that for confidence levels $\alpha = 97.5\%$ and 99% the best trade-off are $\left(\lambda = 0.9, E\left(\widetilde{TNPV}\right) = 160.39, CVaR_{95\%}\left(\widetilde{TNPV}\right) = 138.36,\right)$ and $\left(\lambda = 0.1, E\left(\widetilde{TNPV}\right) = 159.9, CVaR_{95\%}\left(\widetilde{TNPV}\right) = 121.76\right)$ respectively. The results obtained from the max_E_CVaR model enable decision makers to select and schedule project portfolio according to their risk appetite and the weightage they attribute to the risk measure CVaR and the expected measure E_CVaR.

8 Conclusion

Project portfolios are considered as strategic weapons for an organization's success. Thus, project portfolio selection and scheduling optimization is critical for organizations. The present study evaluates strategic alignment scores and risk scores of the identified projects of a dairy firm and ensures that the selected project portfolio aligns with the strategic goals of the organization and is least exposed to risks. Further, it recommends risk-averse approach by adopting the risk measure CVaR as the objective function of the project portfolio selection and scheduling optimization problem with uncertain project cash inflows. A comparison between the output of risk averse model and the risk-neutral model shows that the risk-averse model ensures that the lowest return in the worst scenario is maximized to the greatest extent possible, thereby, yielding higher returns even when the confidence levels are low. The model exploits the diversification approach for risk management and its portfolios contain at least one project from each project category (derivative, platform and breakthrough) which is in accordance with the aggregate project plan suggested by Wheelwright and Clark (1992).The results obtained from the combined compromise model can be utilized by decision makers to select and schedule project portfolio according to their risk appetite and the weightage they attribute to risk-averse and risk-neutral objectives.

A future scope of research lies in applying the proposed risk-averse model in diversified conglomerates that have programs of projects in multiple sectors. The strategic contribution of these programs to the vision of the organization can be assessed to ensure long-term impact on of these programs on organization's growth. A program portfolio selection and scheduling model incorporating varying risk appetite at different stages of the organization's lifecycle can yield insights for long term strategic planning.

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