production cost. Recently developed stochastic models included uncertainty and financial risk expanded to the effect of pricing [15–17]. Tolis and Rentizelas [18] implemented a stochastic programming algorithm without recourse to assess the impact of electricity and CO_2 allowance prices in planning expansions in the power sector under several uncertainties. Koltsaklis et al. [19] used mixed integer programming to determine the optimal planning of a power generation system, which included technology and fuel selection and plant allocation to meet required demand while satisfying emission constraints. They investigated the influence of CO_2 emission price as well as other parameters on their results using sensitivity analyses. Zhu et al. used a hybrid mathematical model incorporating mixed integer programming for the optimal planning of regional municipal energy systems [20,21].

Economic needs and the ongoing trend of liberalization of the electricity markets have stimulated the interest of power utilities players to develop operating models and the corresponding mathematical optimization techniques that effectively address the issue of generation and trading of electric/electrical power under uncertainty [22,23]. Eichhorn and Romisch [24] developed a mean-risk optimization model that maximizes revenue and minimizes financial risk. The variables that revealed the stochastic behavior in the model via their uncertainty include electricity demand, and current and future prices. Azaron et al. proposed an approach for designing supply chains considering uncertainties within it [25]. The multi-objective stochastic program involved minimizing both cost and financial risk. Demands, supplies, and prices are the main variables that imposed uncertainty in the model. Stochastic programming has been used extensively in mitigating financial risks and the effect of uncertainties in supply chain design problems [26–29]. It has also been used in refinery operations planning taking into account uncertain demand under the consideration of the cost of unsatisfied demand and overproduction scenarios [30,31].

Deregulated energy markets and the emergence of centralized physical markets in electric power run by independent system operator organizations have resulted in complexities pertaining to managing market risks in both operations and financial aspects [32]. The unit commitment problem deals with the short-term schedule of thermal units in order to supply the electricity demand in an efficient manner. In this type of model, the main decision variables are generators start-ups and shutdowns [33]. In other words, the problem concerns how to most economically schedule the generating units considering the unit economics, physical constraints and incremental transmission losses such that the operator's total commitment to deliver power is met [34].

In classical investment portfolio theory, optimizing the expected return for a specified level of risk is a well-known problem as optimized in the seminal Nobel Prize-winning work of Markowitz [35]. Three dimensions are addressed in this problem: (1) the expected return (or profit and loss P&L) on each instrument in the portfolio; (2) the risk associated with that profit as measured by the variance in the expected profit by Markowitz's mean variance (MV) model or by other alternate measures of risk, such as value at risk (VaR) or conditional value at risk (CVaR); and (3) the quantity of each instrument held. A measure of risk that goes beyond the information revealed by VaR is the expected value of the losses that exceed VaR, thus termed as CVaR [36]. The CVaR mitigates the shortcomings of VaR while possessing the same meaning [37]. Recently, mean-risk models have attracted attention in stochastic programming [38]. Bagajewicz has shown that a solution that minimizes financial risk at cost minimization target also minimizes the expected value of cost of power generation [39]. Gomez-Villalva and Ramos extended a deterministic optimization model into a two-stage stochastic program to account for risk resulting from energy price uncertainty [40].

If improvements in an existing chemical process are not sufficient to meet business needs, then new technologies can be considered. However, the application of a new technology is always perceived as a potential threat. One of the approaches that help alleviate the risk of investment is minimizing the associated financial risk. Based on an extensive review of the literature, there are virtually no studies that incorporate financial risk management within the context of the well-known problem of electric power planning. This paper proposes a new methodology to include financial risk management, which is incorporated by minimizing the CVaR, in the framework of two-stage stochastic programming for energy planning under uncertainties in demands and fuel price. This presents a sophisticated decision making tool to help support better informed investment decisions.

2. Methodology

This paper introduces a new systematic method for screening, identifying, and evaluating technology integration options, which aim at improving the cost-efficiency of a continuous chemical process. The method is organized in four steps (Fig. 1): (1) business case analysis, (2) process improvement without new technologies, (3) process improvement with the incorporation of new technologies, and (4) financial risk management. The first three steps were covered in a prior paper Ahmed et al. [42]. In this paper the fourth step is described in detail and is demonstrated using the same case study. In the previous work, the technologies used in the case study were identified and the feasibility of their integration into

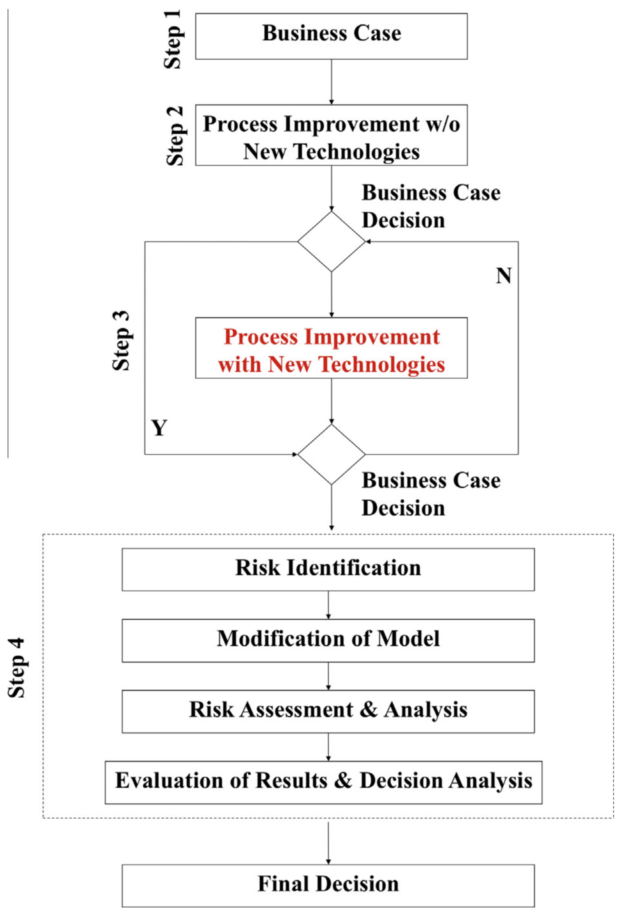

Fig. 1. Summary of steps in the proposed methodology.