Application and Outlook of Prospect Theory Applied to Bounded Rational Power System Economic Decisions

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***Abstract*—Economic decision-making of electric power system plays a vital role in the planning, operation, and transaction of the electric power system. While the achievement of behavioral economics tells us that all the decision-making process with human involvement is not that simple. Limited to human's subjectivity on cognition and decision preference, the decision will become bounded rational. Sufficient knowledge on the behavior of power system economic decisions can improve the accuracy and practicability of decision-making modeling, simulation, and forecasting in power system, as well as improve the social elements in developing a cyber-physical-social system of the power system. Among different behavioral economic theories, prospect theory (PT) wins a wide range of research and application. Thus, PT is first introduced here, and then the application of PT is reviewed in the field of power system economic decisions. What follows is the analysis and discussion on three key issues of current theory application, including function model selection, parameter identification, and application framework establishment. Finally, three possible further research prospects are proposed, including the application of developed theory, the combination of multiple behavioral economics, and the consideration of social elements.**

***Index Terms*—Behavioral economics, bounded rationality, economic decision of power system, prospect theory (PT).**

I. Introduction

With the continuous advancement of the marketization of the power industry, unified and open power market model, flexible pricing mechanism, and diversified smart grid have become the direction of future development [1]. However, while promoting the optimal allocation of power resources, the reform of the power market will also bring more uncertainties to economic decision-making in the power sector.

The uncertain market environment makes the decision-making behaviors of market entities such as generation companies (GENCOs), distributors, and power consumers full of risks. For this kind of risky decision-making problems, in the past, research was conducted under the assumption of "completely rational people", which made the maximization of economic benefits the only goal of decision-making. However, this assumption is too absolute and often goes against some real decision-making phenomena in the power sector. For example, the establishment of a demand-side management (DSM) mechanism can help users reduce electricity costs, but the actual situation is that users are not very motivated to respond. Especially for residential users, most of them value comfort rather than electricity cost. However, in some specific situations, like Earth Hour, a global environmental protection activity held at 8:30 P.M. on the last Saturday of March annually, users may be in response to a call for interrupt their electricity behavior during peak time, to some extent, this is at the expense of his own comfort. In addition, a completely rational GENCO should have the same risk preference for different power allocation decisions in multiple markets. However, due to the different risk conditions of the contract market and the day-ahead market, under a certain profit target, the GENCO will present different risk preferences for different allocation schemes. Similar irrational behaviors are far more than these in the field of power economic decision-making. In order to portray the above-mentioned irrational behaviors, it is necessary to capture the true heart of decision-makers through special means, so behavioral economics can play a guiding role.

Behavioral economics was born in the 1950s, and its initial development is closely related to Herbert Simon. As one of the founders of cognitive psychology, the hypothesis of "bounded rationality" [2] put forward by him has a profound reference significance for the subsequent behavioral economics theories. The hypothesis believes that when people make decisions, due to the constraints of the complex environment and their own cognitive abilities, decision-makers will not be able to accurately understand their own preferences, and the final decision-making

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results are not optimal. This hypothesis strongly promotes the integration of economics and psychology, which has derived many theories, including prospect theory (PT), mental accounting [3], the behavioral life-cycle hypothesis, heuristic bias, self-control problem, etc. Among them, benefiting from the solid theoretical foundation of expected utility theory (EUT), PT has a wider range of application scenarios and scope than other behavioral economics theories. On the basis of our original research [4], this article expands the basic connotation of PT. At the same time, the current application of PT in the electric power field are covered more comprehensively, and some new ideals are put forward for the application deficiencies.

II. Development of PT

Since the PT was put forward, it has developed from the original PT (OPT) [5] to the cumulative PT (CPT) [6], and further developed into the third-generation PT (3G-PT) [7]. In this development process, the framework system of PT has been continuously improved, and the explanatory power of individual actual decision-making process has also become stronger. In the following, the OPT, CPT, and 3G-PT will be introduced step by step.

A. *Original PT*

Before the 1980s, as one of the main tools for studying risk decision-making problems, the EUT has always been regarded as the normative model of rational choice. However, through experimental research, Tversky and Kahneman found that people's actual decision-making behavior under risk conditions deviates from the EUT, such as the certainty effect, the reflection effect, probabilistic insurance, the isolation effect, etc. In order to explain this behavioral deviation, they proposed the OPT.

In the OPT, Tversky and Kahneman divide the individual's decision-making process under risk conditions into two steps: the editing phase and the evaluation phase. In the editing phase, using heuristic methods including coding, combination, segregation, cancellation, simplification, and detection of dominance, people can simplify and standardize decision-making problems to make them conform to the application framework of PT. In the evaluation phase, the utility and probability are mapped through the value function and the weight function, and the decision-maker will finally screen out the decision-making plan with the largest prospect value.

As the two core description frameworks in PT, value function and weight function are originally presented in the form of images, as shown in Figs. 1 and 2. These two images sufficiently explain those behavioral deviations that are contrary to the EUT, and portray the true feelings of the decision makers about utility and probability.

Among them, the value function image highlights the following characteristics of subjective utility.

1) Losses and gains are relative to the reference point.
2) Risk aversion in the face of gains, risk preference in the face of losses.
3) More sensitive to losses than equivalent gains.

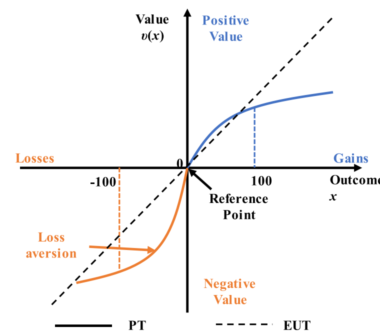

Fig. 1. Value function of OPT.

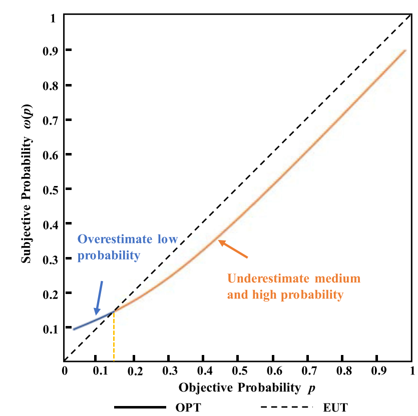

Fig. 2. Weight function of OPT.

The weight function image highlights the following characteristics of subjective probability.

1) Overestimation of small probability events.
2) Subadditivity, namely when involving small probabilities, the weight function will be a subadditivity function.
3) Subcertainty, namely the sum of the weights associated with complementary events is typically less than the weight associated with the certain events.
4) Approaching the boundary of certain events, the probability weight is often ignored or magnified.

B. *Cumulative PT*

On one hand, OPT violates the first-order stochastic dominance. On the other hand, due to its own limitations, it can only analyze at most two nonzero results. However, the above two shortcomings cannot be sidestepped in the analysis of some decision-making problems. Therefore, Tversky and Kahneman borrowed the idea of hierarchical dependence and proposed the CPT. Through the introduction of rank-dependent EUT [8], CPT solves the defects in OPT and improves the image of the weight function, as shown in Fig. 3. On this basis, two mathematical expressions of the prospect function are proposed.

The mathematical description of the value function is denoted as follows:

$$v(x) = \begin{cases} (x - x_0)^{\alpha} & x \geq x_0 \\ -\lambda(x_0 - x)^{\beta} & x < x_0 \end{cases} \tag{1}$$

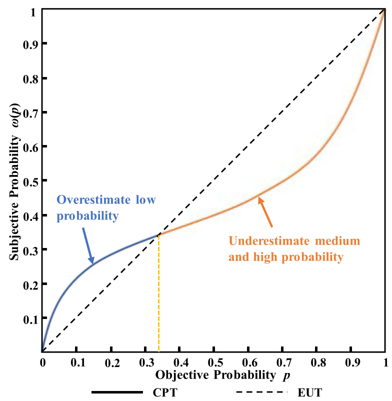

Fig. 3. Weight function of CPT.

where x_0 is the reference point, x is the result of alternative schemes, α and β are the risk attitude coefficients, $0 < \alpha, \beta < 1$, the larger the value of α and β are, the more likely the decision maker is to take risks. λ is the loss aversion coefficient. When $\lambda > 1$, it indicates that decision makers are more sensitive to loss.

The mathematical description of the weight function is denoted as (2) and (3)

$$\omega^+(p) = \frac{p^\gamma}{\left[p^\gamma + (1-p)^\gamma\right]^{1/\gamma}} \tag{2}$$

$$\omega^-(p) = \frac{p^\delta}{\left[p^\delta + (1-p)^\delta\right]^{1/\delta}} \tag{3}$$

where $\omega(p)^+$ and $\omega(p)^-$ are the decision weights of decision makers when they feel gains and losses respectively. p is the true probability of occurrence of event x. γ and δ are the risk attitude coefficients of gain and loss respectively. The smaller the value is, the more likely the decision maker is to overestimate the events with low probability and underestimate the events with high probability.

Different from OPT for mapping a single probability, CPT realizes the mapping of the cumulative probability. Suppose p_i is the probability of occurrence of each candidate result x_i; among them, each candidate result is arranged in ascending order, namely $x_{-m} \leq \ldots \leq x_{-1} \leq x_0 \leq x_1 \leq \ldots \leq x_n$. Therefore, the cumulative weight function can be denoted as (4) and (5)

$$\begin{cases} \pi_i^+ = \omega^+(p_i + \cdots + p_n) - \omega^+(p_{i+1} + \cdots + p_n), 0 \leq i < n \\ \pi_n^+ = \omega^+(p_n) \end{cases} \tag{4}$$

$$\begin{cases} \pi_j^- = \omega^-(p_{-m} + \cdots + p_j) - \omega^-(p_{-m} + \cdots + p_{j-1}), -m < j \leq 0 \\ \pi_{-m}^- = \omega^-(p_{-m}) \end{cases} \tag{5}$$

where $\pi^+(\cdot)$ and $\pi^-(\cdot)$ respectively represent the cumulative decision weights of the "gain" and "loss" areas.

It can be concluded that the final expression of the CPT is as follows:

$$V = \sum_{i=0}^{n} \pi_i{}^+ \upsilon(x_i) + \sum_{j=-m}^{0} \pi_j{}^- \upsilon(x_j). \tag{6}$$

The PT given by Tversky and Kahneman is a functional form of the discrete distribution of event outcomes, while actual research generally assumes that the outcome of alternatives is a random variable that obeys a specific distribution. In response to this problem, Rieger and Wang [9] extended the CPT to the continuous distribution of event outcomes.

In addition to the above-mentioned CPT used to describe objective utility and cumulative probability, many studies often characterize bounded rational behaviors by only using the weighting framework of PT with subjective probability under weighting effect in the form of the following equation:

$$\omega(p) = \exp\left(-(-\ln p)^\theta\right), 0 \leq \theta \leq 1 \tag{7}$$

where θ is the coefficient of rationality that reveals distortion of the objective probabilities caused by people's subjective perception.

In fact, CPT mainly uses some technical means to further improve OPT, while the PT model applied by some scholars in the study of decision-making problems usually refers to the comprehensive framework system integrating OPT and CPT.

C. Third-Generation PT

In order to better explain the phenomenon of "preference reversal", Schmidt and Starmer proposed 3G-PT, addressing the variability of reference point in the PT. In the 3G-PT, the reference point is regarded as a random event, namely the reference event. Gains and losses are also defined as objective states. The specific model is as follows [6]:

$$V(f,h) = \sum\nolimits_i \upsilon\left(f[s_i], h[s_i]\right) \omega\left(s_i; f, h\right) \tag{8}$$

$$\omega(s_i; f, h) = \begin{cases} \omega^+(p_i), & i = m^+ \\ \omega^+\left(\sum_i^{m^+} p_k\right) - \omega^+\left(\sum_{i+1}^{m^+} p_k\right), \\ 1 \leq i \leq m^+ - 1 \\ \omega^-\left(\sum_{-m^-}^{i} p_k\right) - \omega^-\left(\sum_{-m^-}^{i-1} p_k\right), \\ -m^- + 1 \leq i \leq -1 \\ \omega^-(p_i), & i = -m^- \end{cases} \tag{9}$$

where state set $S = (s_i \mid i = 1, \ldots, n)$ corresponds to the objective probability $\Sigma\ p_k = 1$; $f\ [s_i]$ and $h\ [s_i]$ represent the results of event f and h with s_i; $\upsilon(f\ [s_i],\ h\ [s_i])$ is the relative value, used to describe the value of event f relative to reference event h, and calculated by (1); $\omega(s_i;\ f,\ h)$ is the probability weight. Among them, $-m^-$, $-m^-+1, \ldots, -1$ are the state subscripts corresponding to losses, $1, 2, \ldots, m^+$ are the state subscripts of gains, and the calculation of $\omega^+(\cdot)$ and $\omega^-(\cdot)$ are shown in (2) and (3)

Generally speaking, the 3G-PT not only retains the predictive ability of other PT series models but also considers the measurement problem under loss aversion, thereby making up for the gaps in the application of other prospect theories. This has

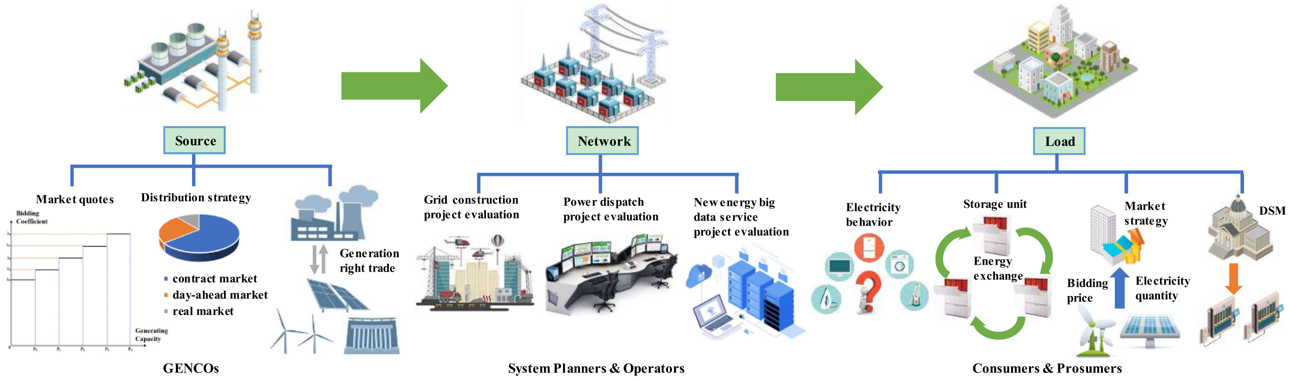

Fig. 4. Current application areas of power system economic decision.

TABLE I
SUMMARY OF PT APPLICATION IN GENCOs' MARKET BEHAVIOR ANALYSIS

Ref. No.	Prospect Theory Applied in GENCO Behavior analysis			Application Effect
	Research Area	Value Function & Parameter Setting	Weight Function & Parameter Setting	
[11]	Optimal bidding problem of generation companies	☑Eq.(1) α=0.88,β=0.88 λ=2.25	☑Eq.(2)(3) γ=0.61 δ=0.67	Compared with the utility function model under fixed risk preference, PT model can help avoid extreme bidding strategies under complete rationality.
[12]	Optimal energy allocation between contract market and day-ahead market	☑ Eq.(1) α=0.88,β=0.88 λ=7	☑Eq.(2)(3) γ=0.61 δ=0.67	Compared with the model based on value function and SP/A theory, PT based model can distinguish GENCOs with different personality characteristics through risk coefficients.
[13]	Optimal decision on both power allocation and bidding strategy	☑ Eq.(1) α=0.8, β=0.8 λ=2.25	☑Eq.(2)(3) γ=0.61 δ=0.67	PT based model was proven to fit dynamic market better, with considering the influence of predicted load, market price and market risk on subjective feelings
[14]	Non-cooperative game of GENCOs	☒	☑Eq.(7) θ: self-setting	Compared with EUT model, PT based model could reduce the probability of bidding failure considering loss aversion.
[15]	Bidding strategy of GENCOs under the framework of evolutionary game	☑ Eq.(1) α=0.88, β=0.88 λ=2.25	☑Eq.(7) θ=0.8	The connection between power generation cost and bidding strategy can be revealed by PT based model with the changing risk appetite of GENCOs.
[16]	Bilateral matching on hybrid power generation rights trading	☑ Eq.(1) α,β,λ: self-setting	☑Eq.(2)(3) θ: self-setting	PT based model could describe the psychological attitude of bounded rational entities to the risk of bilateral matching.

☑:corresponding function was applied in relevant work.☒: corresponding function was not applied in relevant work.

certain academic reference value for research under uncertainty and risk decision-making.

III. State-of-Art Application of PT in Power Economic Decision-Making

PT has been widely used in many branches of economic and scientific fields [10], but its application in power industry is still in the exploratory stage. In order to give sufficient play to the application value of PT in power economic decision-making, it is necessary to have a comprehensive understanding of the current research situation.

In fact, the economic decision-making of the power system runs through each link from power generation to power consumption, as shown in Fig. 4. Due to some inherent uncertain factors in the operation of the power system, these power system economic decisions are often described as risky decision-making problems, which also create prerequisites for the application of PT.

A. PT-Based Decision-Making in the Field of Power Market

When participating in market competition, GENCOs lack complete information of the opponent's decision-making and the entire market, and also they have different risk preferences under the influence of psychological expectations. Therefore, market decision-making behavior of GENCOs can be described as bounded rationality. In order to better simulate market competition behaviors that fully consider the psychological factors of GENCOs, some scholars have begun to study how to establish market decision models based on PT to help GENCOs better understand their own and the other party's decision-making behavior, so as to help them make more practical decision plans in line with psychological expectations.

The state-of-art PT-based application in the field of GENCOs' market behavior analysis is summarized and listed in Table I. Current research mainly focused on strategies of market bidding, energy distribution in multiple markets, and generation rights trading.

An optimal bidding problem of GENCOs was discussed in [11] based on the CPT. After discretizing the range of the GENCOs' quotation, the mapping relationship between the probability and the weight of the bidding scheme in the "gain" and "loss" had been established. Therefore, a quotation optimization model with expected profit as the reference point was constructed. By analyzing the optimal quotation curve under different expected profits and risk preferences, the feasibility of PT was verified to

TABLE II
SUMMARY OF PT APPLICATION IN OPTIMAL SELECTION OF POWER SYSTEM PLANNING PROJECTS

Ref. No.	Prospect Theory Application in Optimal Selection of Power System Planning Projects			Application Effect
	Application Area	Application of Value Function	Application of Weight Function	
[17]	Optimal selection of planning schemes for power grid with high penetration intermittent generations	☑Eq.(1) Don't mention	☑Eq.(2)(3) Don't mention	The model based on PT can help avoid the disorder of ordering scheme caused by risk attitude evaluation errors.
[18]	Investment decision of power grid construction project portfolio based on multi-attribute indices	☑ Eq.(1) α=0.88,β=0.88 λ=1.5	☑Eq.(2)(3) γ=0.61 δ=0.67	The proposed model describes the pros and cons of attribute values more precisely by using the prospect value.
[19]	Multi-attribute investment ranking of power grid project construction	☑ Eq.(1) α=0.88,β=0.88 λ=2.25	☑Eq.(2)(3) γ=0.61 δ=0.68	Compared with EUT Model, PT model considers the dynamic change of risk appetite in the assessment to make investment decisions in line with market laws.
[20]	Evaluation of joint dispatch schemes for cascade hydropower stations	☑ Eq.(1) α=0.88,β=0.88 λ=1.1	☑Eq.(2)(3) γ=0.61 δ=0.68	Compared with the traditional TOPSIS Rank model, PT model incorporates the repulsive psychology to extremely bad indicators into the evaluation system.
[21]	Benefit evaluation of multi-energy microgrid solutions	☑ Eq.(1) α=0.88,β=0.88 λ=2.25	☒	Compared with the non-prospect model, PT model considers the impact of decision-makers' subjective preference on evaluation which improves the practicality of the results.
[22]	Comprehensive evaluation of new energy big data service projects	☑ Eq.(1) α=0.88,β=0.88 λ=2.25	☒	The model based on PT overcomes the shortcoming that the subjective risk propensity of decision makers can take an impact on the comprehensive evaluation.

☑:corresponding function was applied in relevant work. ☒:corresponding function was not applied in relevant work.

study the problem of power supplier's quotation decision. Aiming at achieving optimal energy distribution between contract market and day-ahead market, a profit function with normal distribution characteristics was constructed in [12] on the basis of predicting the probability distribution of electricity prices in the two markets. Based on the expected profit as a reference point, a different value function and weight function were established for the GENCO to perceive "gain" and "loss", thereby establishing a power generation optimization model for power distribution in two markets, breaking the unreasonable assumption of traditional risk decision theory simply regarding decision makers as risk preference or risk avoider in isolation. Sun and Jiang [13] proposed a comprehensive decision-making optimization model for GENCOs addressing both quotation and energy allocation decisions. By introducing coefficients related to electricity price and risk levels to simulate the market environment, the psychological and behavioral characteristics of decision-makers were analyzed under different forecast load, unit operating cost, and day-ahead market environment. To study the quotation strategy of GENCOs, a noncooperative game model of power generation entities in the real-time and standby markets was established in [14]. This work applied the weight function of PT to describe the objective probability as the probability of other participants' subjective decision making. Sensitivity analysis showed the merits of PT-based model compared to EUT. Li *et al.* [15] considered the impact of environmental conditions on the subjective judgment of power suppliers' quotations. Based on CPT, a GENCO bidding strategy model with optimal response dynamic mechanism was established by using improved Bayesian to simulate the evolution process of GENCO's bid winning probability. This application case study implied CPT based method could reflect the real bidding behavior of GENCOs with continuously adjusting their own strategies according to their own experience and market information. On the aspect of behavior analysis in generation right trading, a hybrid generation right trading matching model was proposed in [16] with a comprehensive attribute index evaluation system of electric energy. Value function and weight function of PT were used to evaluated price and linguistic indicators, and the matching scheme with the largest overall prospect value was selected as the result of the hybrid power generation rights transaction. Simulation analysis showed that the PT-based method could improve the environmental protection and output stability of the alternative electricity on the basis of satisfying the transaction income of the participants.

B. PT-Based Decision-Making in the Field of Network Planning

Power network planning needs to take various indicators into consideration comprehensively. While system planners have different subjective judgment standards, thus pros and cons ranking of candidate schemes is also a bounded rational problem. For this reason, the traditional investment evaluation method is impractical, thus many researchers introduced PT to deal with the bounded rationality in network planning decision, as listed in Table II, including grid construction projects, power dispatch projects, and big data service projects.

Based on the evaluation index system construction of power grid planning schemes integrated with high-penetration of intermittent power supply, an evaluation decision method of power grid planning schemes was proposed in [17] with value function and weight function of each evaluation indicator constructed combining the subjective preference and risk tendency of decision makers. By using the multicriteria compromise solution ranking method, PT-based VIKOR method could help avoid the disorder of the ordering scheme caused by risk attitude evaluation errors. The authors of [18] regarded the investment decision-making of the power grid construction project portfolio as a multiattribute decision-making problem with indicators of four data types: deterministic, interval, probabilistic, and fuzzy. The prospect value of each indicator composed of value function and weight function were constructed by mapping gains and

TABLE III
SUMMARY OF PT APPLICATION IN DECISION BEHAVIOR ANALYSIS ON THE DEMAND SIDE

Ref. No.	Prospect Theory Application in Decision Behavior Analysis on the Demand Side			Application Effect
	Application Area	Application of Value Function	Application of Weight Function	
[23]	Active consumer behavior under variable electricity pricing	☒	☑Eq.(7) θ: self-setting	Compared with EUT model, PT model can help capture the actual energy consumption behavior of consumers with different individual preferences.
[24]	Non-cooperative game between customer-owned storage units	☒	☑Eq.(7) θ: self-setting	Compared with EUT model, PT model can help retail companies avoid losses in revenues and undesirable loads due to incorrect analysis of customers' real behavior.
[25]	Energy exchange between microgrids	☒	☑Eq.(7) θ: self-setting	Compared with EUT model, PT model can help analyze the real behavior preference of the microgrid under different battery levels to avoid the impact of user subjectivity on the trade.
[26]	Smart grid energy management under stochastic dynamics	☑ Eq.(1) α=0.5,β=0.3 λ: self-setting	☑Eq.(7) θ: self-setting	Compared with EUT model, PT model reveals the connection between prosumers' energy regimes and loss sensitivity.
[27]	Bidding behaviors of prosumers in power market	☑ Eq.(1) α=0.88,β=0.88 λ: self-setting	☑Eq.(7) θ: self-setting	Compared with the EUT model, PT model can help analyze how psychological factors affect prosumers' bidding behavior to capture their subjective perception of the bidding results.
[28]	Energy trading between smart grid prosumers	☑ Eq.(1) α=0.7,β=0.1 λ=5	☑Eq.(7) θ=0.6	Compared with the traditional game theory model, PT can help realize subjective behavior modeling of prosumers considering the intermittency of wind energy generation.
[29]	Design of distributed power trading mechanism based on P2P contract	☒	☑Eq.(7) θ: self-setting	Compared with EUT model, PT model reveals the dynamic changes between the objective market price and the subjective behavior of prosumers.
[30]	Demand-side management	☒	☑Eq.(7) θ: self-setting	Compared with EUT model, PT model reveals that the DSM participation level and grid load has significant relationship with rationality level of the players and their risk aversion tendencies.
[31]	Design of incentive-based demand response program	☑ Eq.(1) α=0.88,β=0.88 λ=2.5	☒	PT model is used to verify the control effect of the proposed demand response program on the consumption pattern of the bounded rational population.

☑: corresponding function was applied in relevant work. ☒: corresponding function was not applied in relevant work.

losses with their corresponding probabilities. With PT-based VIKOR method, the optimization of project portfolio could be conducted, meticulously describing the different subjective judgments of the decision makers on different indicator types. Another grid construction project evaluation method using PT-based analytic hierarchy process was proposed in [19] with the goal of maximizing the comprehensive prospect value of the project, considering dynamic risk appetite change of decision makers during the assessment in line with market laws. A cascade hydropower station joint dispatch rating method based on PT was proposed in [20]. Compared with the traditional technique for order preference by similarity to an ideal solution (TOPSIS) method, the program ranking based on PT fully considered the risk attitude preference of decision makers on different indicators, resulting in higher decision makers' subjective satisfaction.

Different from the above-mentioned evaluation system involving both value function and weight function [17]–[20], PT applied in [21] and [22] comprehensively weighted each indicator subjectively and objectively based on the improved AHP method and entropy weight method, combining with the value function to derive the corresponding evaluation system. Where a micro-grid benefit evaluation decision with the PT-based VIKOR method was proposed in [21] to sort the different schemes to improve the accuracy and reliability of the evaluation result. Considering economic, social services, technical and environmental benefits, a comprehensive benefit rating system based on PT and TOPSIS method was established to choose the optimal new energy big data service projects in [22]. This method could reduce the impact on the decision brought by the subjective risk propensity of decision makers.

C. PT-Based Decision-Making on Demand Side

With the development of distributed generation and smart grids, as well as the demand side market mechanism, a large number of "passive" electricity consumers have gradually turned to "active" load of power grid with both adjustable load resources and distributed generation resources. To a certain extent, the dispersive large amount of resources on demand side indeed play vital role in increasing the flexibility of power system. However, the analysis on various behaviors of massive bounded rational consumers is also a big challenge to mechanism designers, system operators, and retail companies. Many scholars are dedicated to tackle this problem with PT, as listed in Table III. As shown in the table, it can be found that the PT-based behavior modeling has been applied in the field of aggregator and microgrid pricing scheme [23]–[25], demand-side strategy of energy distribution [26], quotation [27], transaction [28], [29], and mechanism design [30], [31].

A Stackelberg game model between active consumers and aggregators was proposed to simulate and analyze the interaction behavior in [23]. With the goal of maximizing profits and improving distribution network voltage quality, the aggregator was described as a leader, with the hybrid pricing strategy under the estimation of active users' response based on PT. The subjective judgment on the probability distribution of electricity prices by active consumers, comprehensively considering economy, comfort, and grid stability, was described by weight function to verify the feasibility of guiding the irrational behavior. Wang *et al.* [24] proposed a new framework for energy management in smart grids based on PT. With considering the subjective evaluation of each user's mixed strategy against the opponent, the noncooperative game between energy storage unit owners was simulated, and the result showed that the user's bounded rationality had a great effect on their charging and discharging behavior, as well as the total revenue and expected load of the retail companies. This impact would help companies to design better electricity price and penalty coefficients to stimulate users. An energy exchange game between microgrid and power plants was formulated as a PT-based static game in [25], taking the influence of the microgrid operators' bounded rational behavior on the energy exchange into consideration. The numerical study showed that the micro-grid exhibits different sales and purchase tendencies under different power levels, providing a reference for energy market designers to establish a reasonable energy price standard to avoid subjective influence on micro-grid transactions. In [26], a random game model was formulated to simulate the interaction between prosumers to support best smart grid energy allocation strategy, dealing with the subjective feelings of prosumers with PT. Compared with the traditional EUT model, the proposed method could reveal the connection between prosumers' energy regimes and loss sensitivity.

As for the competitive market environment on the demand side, a bidding model of prosumers based on PT was proposed to capture users' subjective perception of bidding results [27]. The parameter differences in prospect functions were analyzed to distinguish rational, conservative, neutral, and active prosumers, showing the readers the effect of psychological factors on prosumers' bidding behavior. By comparing the results of the noncooperative Nash equilibrium under three models of prosumer, i.e., with original utility, value function, and probability weighting, El Rahi *et al.* [28] constructed three smart grid prosumer models, the magnification of punishment by the last two prospective frameworks was verified to take subjective behavior caused by the intermittency of wind power into account. A distributed power trading mechanism was designed based on P2P contracts in [29] with a PT-based bidding model for prosumers considering their subjective prediction behavior on the objective market transaction prices.

DSM has gradually become an important smart grid function to support the efficiency, secure, economic operation of main grid. The behavior analysis on the demand side loads is the first step to ensure the efficiency of the designed DSM mechanism. Some scholars try to use the results of user games under the framework of PT to verify the rationality and feasibility in the field of DSM mechanism design [30], [31]. Through establishing a noncooperative game model, the DSM participation of users were studied in [30], with weight function applied to characterize users' subjective judgment on the mixed strategies of other participants. Result showed that users' decisions on participation in DSM were correlated with their rationality and risk aversion tendency, and distinguished the potential factors of low participation in realistic DSM programs. To study the performance of the designed demand response (DR) program, noncooperative PT-based game model was introduced to obtain an optimal strategy of incentives and penalties to guide the users' consumption [31]. The application result verified the control effect of charging mechanism design on user's electricity consumption pattern.

IV. Issues of PT Application in Electric Power Field

Through the above summary of the application of PT in the power field, it can be clearly found that the mathematical description of the value function and weight function in different application scenarios is very simple, and the parameter selection that represents the rationality of decision makers also has certain limitations. In order to describe the limited rational behavior of power decision makers more truthfully, the above two problems cannot be avoided. On this basis, the application framework of PT in the power field needs to be proposed to summarize the existing research and provide a reference paradigm.

A. Selection of Prospect Function Model

Based on the mathematical expressions of the value function and weight function, PT realizes the transition from abstract description to concrete quantification of bounded rationality. Because the uncertain factors faced by risk decision-making problems in different fields have certain differences, there has been controversy about the optimization of the prospect function. It can be found from Table IV that when studying some specific problems, the value function and weight function of other mathematical forms will be more appropriate for the description of subjective utility and probability.

Similarly, the uncertain factors faced by GENCOs, distributors, and power users in the power sector are different when facing different decision-making problems. Therefore, the value function and weight function established by Kahneman and Tversky will not be universal. At present, the power economic decision-making model based on PT has not yet involved the research on the mathematical expression of prospect function, which will be the next issue that needs to be focused on.

B. Measurement and Parameter Identification of Psychological Factors

The choice of risk attitude coefficient and loss aversion coefficient in the prospect function realizes the distinction between people with different preferences, which plays a decisive role in quantifying the rationality of decision makers. However, in the field of electric power, there is no in-depth research on the identification of the psychological parameters of the prospect function. It is mainly through subjective setting or directly using the parameters given by Kahneman and Tversky in the CPT ($\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.69$, $\delta = 0.61$). Referring to the research situation of PT in the field of transportation, it can be found that some scholars have carried out research on parameter estimation for travel time value, road network balance, and route selection, as shown in Table V [38].

From the research results in Table V, it can be found that the parameters proposed by Kahneman and Tversky are not universal and need to be determined according to relevant

TABLE IV
OTHER MATHEMATICAL EXPRESSIONS OF VALUE FUNCTION AND WEIGHT FUNCTION

Function	Research Direction	Proposing Scholar and Year	Mathematical Expression	Parameter Meaning
Value Function	Equity Premium Puzzle [32]	Benartzi and Thaler(1995)	$\upsilon(x)=\begin{cases} x, x\geq 0 \\ \lambda x, x<0 \end{cases}$	λ: Loss aversion coefficient
	Financial Risk-return Problem [33]	Bell(1995)	$\upsilon(x)=\begin{cases} x-\frac{\alpha}{2}x^2, x\geq 0 \\ \lambda\left(x-\frac{\beta}{2}x^2\right), x<0 \end{cases}$	α, β: Risk attitude coefficient λ: Loss aversion coefficient
	Portfolio Selection Problem [34]	Giorgi and Hens(2006)	$\upsilon(x)=\begin{cases} -\lambda^+e^{-\alpha x}+\lambda^+, x\geq 0 \\ \lambda^-e^{\alpha x}-\lambda^-, x<0 \end{cases}$	$\alpha\epsilon(0,1),\lambda^+>\lambda^->0$ Loss aversion coefficient: $\lambda=\frac{\lambda^-}{\lambda^+}$
Weight Function	Preference Axiom Research [35]	Prelec(1998)	$\omega(p)=\exp\left(-(-\ln p)^{\alpha}\right)$	α: Rationality coefficient $0<\alpha<1$
	Risk Choice [36]	Lattimore et al.(1992)	$\pi_i=\frac{\alpha p_i^{\beta}}{\alpha p_i^{\beta}+\sum_{k=1}^{n}p_k^{\beta}}$	β: Rationality coefficient
	Shape of the Weight Function [37]	Gonzalez and Wu(1999)	$\omega(p)=\frac{\delta p^{\gamma}}{\delta p^{\gamma}+(1-p)^{\gamma}}$	δ: Control the elevation of the curve γ: Rationality coefficient

TABLE V
PARAMETERS OF DIFFERENT RESEARCH IN TRANSPORTATION AREA

Research Direction	Different Classification	Value Function			Weight Function	
		α	β	λ	δ	γ
Transportation network [39]	/	1.09~1.10	1.09~1.10	1.27~1.37	0.82~0.84	0.82~0.84
Time value [40]	Morning peak	/	/	0.76	/	/
	Evening peak			1.62		
	Other time periods			1.68		
Path choice [41]	Risk preference	0.43	0.45	1.65	/	/
	Risk neutral	0.34	0.49	1.36		
	Risk aversion	0.26	0.41	1.08		
Path choice [42]	/	0.37	0.59	1.51	0.74	0.74

experimental data in various fields. Experimental economics methods based on physics and engineering experiments can obtain experimental data related to psychological factors, but it has problems such as high experimental design requirements, high experimental costs, and difficult process control [43]. Chen [43] proposed two implementation paths for behavioral economic statistical analysis by fusing statistical analysis with behavioral economics: one was to develop a statistical analysis model suitable for multiple data structures, and the other was to structure unstructured data and incorporate it into the existing statistical analysis system. As a classic theory of behavioral economics, this idea of using statistics to analyze big data and identify psychological factors also had reference significance for PT.

In the electric power field, due to the extensiveness of the power user group, the data sample size is large enough, which provides a shortcut for identifying and measuring the psychological factors of power users, but it also leads to the difficulty of data screening and division. Li *et al.* [44] described the related applications of data mining in power demand-side management. Based on the three major data mining technologies of probability and mathematical statistics technology, database technology and artificial intelligence technology, the application of data mining technology was explained from the three perspectives of demand-side response, orderly power consumption, and energy efficiency management. Aiming at the identification of the psychological factors of power decision makers, these data mining techniques provided the possibility for rapid screening of relevant data.

C. *Construction of PT Application Framework*

In addition to the core problems of prospect function models and parameter estimation, it is also important to establish a research framework for power economic decision-making problems. Since the relationship between EUT and PT is not a complete substitute, and other methods need to be used to weight objective probabilities for some specific problems. Therefore, the existing applications can be divided into three aspects according to the degree of emphasis on the subjective utility and probability of the decision-making problem: using value function only, using weight function only, and combining value function and weight function.

For the evaluation of project benefits such as in [21] and [22], subjective weights need to be determined through expert opinions and user needs, so only the value function is needed to describe the subjective utility. The authors in [14], [24], [25], and [30] usually need to characterize the game behavior between decision makers. Game participants will have subjective judgments about the probability of other players' mixed strategies, but the ultimate goal is to maximize their own interests, so only a weight function needs to be introduced to describe the subjective probability. For most economic decision-making problems in the power field, the subjective judgments of utility and probability of bounded rational people will be considered at the same time. At this time, a model that comprehensively uses value function and weight function will be closer to the behavior of real decision makers.

The above-mentioned classification of existing applications in the electric power field provides an idea for the establishment of a PT application framework, but how to establish a complete application framework to provide a research paradigm still needs to be explored in depth.

V. Prospect of Portraying Bounded Rational Behavior

At present, the description of bounded rational behavior in the power field is mainly through the traditional PT framework. However, the model under this framework still cannot fully simulate the real behavior of bounded rational people. Thus, we put forward three new assumptions to portray the bounded rational behavior, including the application of the 3G-PT, the combination of multiple behavioral economics and the consideration of social factors.

A. Assumptions on the Application of Power Economic Decision-Making Based on the 3G-PT

The 3G-PT better explains the "preference reversal" by introducing random reference points, but it also makes the model more complicated. Therefore, the application of this theory in various fields is not extensive. However, when facing some specific power decision-making problems, the reference point of the decision maker's heart will often change with the different decision-making environment. For example, when the outdoor temperature and weather conditions are different, the resident users will have different perceptions of comfort, and the user's electricity consumption behavior will be based on different comfort reference points. When making the optimal decision-making of power planning projects, the judgment of fuzzy indicators is random, so the reference point will also be dynamic. There are many similar random reference point problems in the field of power decision-making.

Jin *et al.* [45] proposed an interval multiattribute decision-making method based on evidential reasoning and 3G-PT, and verified the effectiveness of the method by using the power system operation scheme selection problem. The next thing that needs to be explored is how to use the 3G-PT in the field of power decision-making to extend the description of bounded rational behavior to aspects that are not currently involved.

B. Combination of Multiple Behavioral Economics

Different behavioral economics theories have different emphases when portraying the true decision-making psychology of people with bounded rationality. Therefore, a model based on a single theory will not be able to cover all the subjective judgments of decision-makers, so it needs to be modified in conjunction with other behavioral economics theories.

Considering that the wealth level of decision makers will affect the value judgment of individuals under uncertain conditions, Wang [46] improved the coding process of PT by introducing mental accounting. The maximum loss value that a personal mental account can bear was used as a measure of the degree of risk avoidance of decision makers, which realized the value correction in the original coding process. So that the final constructed value function could more truly describe the value judgments of different types of decision makers. Jiang *et al.* [47] applied multiple mental accounts under the value function framework to the field of electricity, establishing a bi-layer portfolio selection model for electricity retailers under quota obligation of renewable portfolio standard. In order to fulfill the quota obligation, electricity retailers needed to allocate investment portfolios among three strategies of different risk levels: purchasing renewable energy source, purchasing renewable energy certificates, or paying fines. Different investment strategies reflected the multiple risk preferences of individual retailers, which needed to construct multiple mental accounts to achieve risk stratification. The value function based on different minimum expected returns realized the quantification of differences between different mental accounts.

Trying to build a framework that integrates a variety of behavioral economics theories to provide a reference for studying power economic decision-making issues, which will be a promising development direction in the future.

C. Bounded Rational Behavior Characterization Considering Social Elements

PT focuses more on the description of subjective evaluation under bounded rationality, but in reality, people's behavior is not only induced by psychological factors but also affected by the surrounding social environment. Wang *et al.* [48] put forward a research framework of power user behavior model by combining sociology and psychology, which provided relevant ideas for the "physics-information-society" deeply coupled power system modeling. The research analyzed user behavior from five aspects: behavior subject, behavior environment, behavior means, behavior pattern and behavior utility, and further extended to cluster behavior and predictive behavior. The multidimensional research framework summarized in this document provided a clear research direction for the characterization of bounded rationality based on social factors. The next thing to do is to transform the abstract expression of user behavior into a concrete mathematical model.

VI. Conclusion

The power system is a complex system full of uncertainties. Therefore, when people involve into power economic decisions, bounded rationality of the decisions must be inevitable. The birth of PT provides a theoretical basis for the study of bounded rationality. Current related research on the three important links of power system, including power generation, power grid, and power demand side, has shown the feasibility of PT in the power field. However, the research on PT applied in power system is still in its infancy. Refer to the application of PT in other fields and its own theoretical characteristics, three application issues in electricity economic decision are proposed, including prospect model selection, prospect parameter identification and application framework establishment. At the same time, combined with the development of PT, the advantages of other behavioral economics and the influencing factors of behavior, we put forward three promising research directions, including the application of the 3G-PT, the combination of multiple behavioral economics and the consideration of social factors. Thus, there are still many pending challenges to make the theory more practical in the power field.

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